Chapter 3

Networks in the board of directors: A choice set consideration approach

Basile Dubois
Toulouse School of Economics
basile.dubois@tse-fr.eu

Toulouse School of Economics

Abstract

Using over 70,000 first-time director appointments from 1990 to 2020, I reassess the role of professional connections in the board selection process. While previous literature suggests that direct ties to incumbent directors increase the likelihood of appointment, I show that this effect is overstated when firms draw from segmented candidate pools, such as industry-specific networks. I develop a two-stage model in which the probability of being considered depends on observable characteristics, and the board selects from among the considered candidates. Empirically, I find that candidates with broader professional networks are significantly more likely to be shortlisted and appointed, consistent with the hypothesis that networks serve as screening tools. In contrast, direct personal ties to the board have no positive effect once consideration is modeled, and are associated with relatively lower odds of appointment. Supporting evidence from board committee appointments suggests that personal connections and favoritism are unlikely to explain the observed patterns. The results imply that prior estimates conflate a candidate's relevance with their probability of appointment. In practice, boards appear to prefer candidates with broad, well-documented experience over those with personal ties to insiders.

3.1 Introduction

The board of directors is a central institution in modern corporate governance. It is tasked with overseeing management on behalf of shareholders, while also providing the firm with expertise and strategic guidance. Board members operate collectively, and their decisions shape the direction of the firm. Board appointments are highly consequential but rarely transparent: positions are seldom advertised, and nominees are typically selected by the existing board with input from the CEO. In practice, shareholder votes almost always endorse the board's proposed slate.

Many factors influence board recruitment, but they are difficult to disentangle. Firms have an incentive to appoint capable directors who can provide oversight and strategic guidance. Shareholders may value directors who are independent from management but familiar with the firm's operations or industry. At the same time, CEOs may prefer directors who are supportive of their leadership and unlikely to challenge internal decisions. These competing objectives make it difficult to interpret the role of preexisting relationships. On one hand, shared backgrounds and professional familiarity may improve coordination and reduce friction on the board. On the other hand, connections may help screen for ability: boards may rely on their networks to identify candidates with the right skills and fit. But ties may also reflect cronyism or favoritism if board members or CEOs use the appointment process to reward allies and entrench themselves.

Importantly, it is an empirical fact that personal connections are a strong predictor of who gets appointed. In corporate boards, academic appointments, and political nominations alike, current members tend to select people they know. Previous research has documented strong positive associations between board appointment outcomes and personal ties to incumbents, and often interprets this as evidence of favoritism, insider access, or cronyism.

This paper offers a different perspective. I argue that candidates with personal ties to the board often appear more likely to be appointed, not because of the tie itself, but because the pool of suitable candidates with the necessary skills, experience, and background is small and disproportionately likely to include individuals connected to sitting board members. For illustrative purposes, let us take academia as a reference. Suitable candidates for a Chicago Booth faculty position are drawn from a small group of eminently qualified economists who are likely to know faculty at Booth through past placements, editorial relationships, or through their doctoral studies. In this setting, personal ties reflect pool structure, not preferential treatment. Standard models that ignore this selection process overstate the importance of personal connections.

I formalize this idea in a two-stage structural model of board selection. In the first stage, firms form a consideration set based on observable characteristics, including candidates' professional network size, experience, and connections with the existing board. Importantly, boards with larger network sizes are mechanically more likely to consider connected candidates. In the second stage, firms choose a candidate from that set. This framework distinguishes between a candidate's relevance to the search and their likelihood of being picked, conditional on being considered. A simple theoretical model and simulation exercise illustrate that failing to account for consideration can create upward bias in estimated effects of direct connections, even if those ties play no causal role in the final decision.

I estimate the model on approximately 70,000 first-time director appointments between 1990 and 2020, using BoardEx data linked to CRSP-Compustat. The empirical results support the model's core predictions. Candidates with broader professional networks are significantly more likely to be shortlisted and appointed, consistent with the hypothesis that networks act as screening tools: a larger network increases the likelihood of gathering credible references. In contrast, direct personal ties to the board have no positive effect once consideration is modeled, and are often associated with lower odds of appointment. This pattern holds in the context of committee appointments, where the full choice set is observable. Specifically, personal ties to the board lower the odds of board appointment by 60% conditional on being considered, and lower the odds of committee appointment by 8% conditional on being appointed to the board. If board members were exchanging appointments for favors with their personal connections, we would expect the opposite.

These findings suggest that prior estimates of ”network effects” in board appointments can be explained by the informational and screening role of networks, rather than by interpersonal favoritism. Once the distinction between who is considered and who is ultimately chosen is made explicit, it becomes clear that pre-existing relationships have limited impact on appointment probabilities, once candidate quality and experience are accounted for. In particular, the analysis highlights that past industry experience is the strongest predictor of board appointment, while prior service as a supervisory director is the most important factor for committee selection.

3.1.1 Relation to the literature:

I model board recruitment using tools from the product market literature, where discrete choice frameworks have long been used to recover preferences over alternatives defined by observable attributes (Berry et al., 1995; Nevo, 2001b; Draganska and Jain, 2004). In this setting, candidates are characterized by a vector of features, such as experience, education, or network size, and firms value these characteristics when selecting among potential directors. Importantly, the valuation of candidate attributes may vary across firms depending on their characteristics, reflecting heterogeneity in firm-level needs and governance environments.

Building on this foundation, I then adopt a structural two-stage framework inspired by Goeree (2008) and Abaluck and Adams-Prassl (2021), in which I separately model (i) which candidates are considered for appointment and (ii) which considered candidate is ultimately chosen. This distinction between consideration and choice is central to the empirical strategy: it allows me to recover the structural determinants of board selection while accounting for the fact that firms choose from a subset of candidates. This paper contributes to three main strands of the corporate governance literature: board appointments and monitoring, connected boards, and CEO succession.

The first strand connects board appointments to the board's monitoring function. Hermalin and Weisbach (1998) show that board independence tends to decline as CEO tenure increases, suggesting a substitution between CEO ability and oversight. They also emphasize that boards play a central role in CEO succession, implying that director turnover is linked to broader governance transitions. Following a leadership change, directors affiliated with failed candidates often depart, and the new CEO typically has limited bargaining power. As a result, outside or independent directors are more likely to be appointed early in a CEO's tenure. Rosenstein and Wyatt (1990) further show that the nomination of outside directors is associated with positive market reactions, reinforcing the monitoring role of independent appointments. This line of work laid the groundwork for post-Enron governance reforms, such as the Sarbanes–Oxley Act in the U.S. and the AFEP–MEDEF code in France, which impose limits on insider representation and emphasize board independence. As these rules narrowed the scope for insider appointments, attention increasingly turned to the role of connected directors and board homogeneity.

A second strand of literature focuses on network-based appointments and social proximity between candidates and board members. Kramarz and Thesmar (2013) study the case of French Grandes Écoles to show that directors who are part of the same social network as the CEO are more likely to be appointed to the board. These connections are associated with lower turnover, higher pay, and worse acquisitions, suggesting that social proximity can undermine governance. Berger et al. (2013), using data on German banks, find that boards exhibit homophily: candidates who share ties, gender, or age with incumbent directors are more likely to be appointed and retained. Boards also display homophily when considering director succession, as directors who are similar to the board enjoy longer tenures. They find weak evidence of reduced profitability when the board displays a high number of social ties. Cai et al. (2021), using BoardEx, show that candidates are especially likely to be connected when boards already include a high share of coopted directors or long-tenured CEOs. Moreover, boards with a larger fraction of independent directors also tend to recruit more connected directors. They also show, in a separate binary logistic regression, that firms are more likely to recruit candidates who are connected to the CEO or who exhibit a longer past relationship to a member of the board. Similarly, Liu (2010) finds that better-performing firms are more likely to appoint outside directors and that outside directors typically replace departed outsiders. Using a SURE setup, she shows that larger firms and better-networked CEOs are more likely to appoint connected directors, while CEOs with shorter tenure are more likely to appoint non-connected directors. Collectively, these studies document a strong empirical link between personal ties and board selection, but they typically rely on single-stage specifications that do not account for how candidate pools are formed.

The third strand focuses on CEO succession. As the qualified candidates are few, the choice set is more plausibly recovered in this context. Liu (2010) estimates logit models of CEO turnover and appointment, showing that connected candidates are more likely to be hired and retained. Wang (2020) finds that while connected candidates are more likely to be appointed, firm performance increases when a connected outsider is appointed, while it decreases when a connected insider is appointed. This suggests that connections help screen for ability in external searches, but distort incentives when applied to known insiders.

My contribution is twofold. First, I develop a flexible structural framework inspired by the consideration set literature to jointly estimate the formation of the candidate pool and the final selection. This allows me to recover unbiased estimates of board preferences by isolating the bias introduced by choice set composition. Second, I leverage a large dataset spanning over 70,000 director appointments over 35 years to quantify the relative importance of different observables in the recruitment process. This framework sheds new light on which characteristics boards actually value. For example, I can estimate whether firms favor connected candidates for their ties with insiders or for their broader networks. Because candidate network size is valuable in itself, and because networked candidates are more likely to be personally connected to the board, the model accounts for a key source of misidentification in standard approaches.

The remainder of the paper is organized as follows. Section 3.2 describes the data. Section 3.3, introduces the model. Sections 3.4 and 3.5 present the estimation strategy and results. Section 3.6 uses committee appointments as a sanity check. Section 3.7 concludes.

3.2 The dataset

I construct a matched sample spanning 35 years (1990–2025) by combining BoardEx , which provides detailed information on individual directors and their career histories, with CRSP–Compustat, which covers firm-level financials and market characteristics. The resulting dataset includes, for each firm-year, both the characteristics of the incumbent board and the characteristics of all director appointments, as well as firm financials.

The BoardEx dataset is specifically focused on mapping the professional networks and careers of business executives. It provides detailed information about firms' board composition and individual director profiles, including past positions, education, age, gender, dates of service, as well as partial data on club memberships, nonprofit board affiliations, and other organizational ties. From each individual's employment history and extra-professional activities, BoardEx comprehensively captures professional and educational connections, and partially covers formal networks such as alumni associations, religious congregations, academic fellowships, and professional bodies.

However, BoardEx has notable limitations. Because it primarily targets business executives, its coverage of firms beyond board composition is often sparse and less reliable. Moreover, the dataset's construction leads to incomplete board information for some firms: a firm is either directly profiled (which results in comprehensive board data) or indirectly profiled through an individual director's employment history, resulting in partial coverage. Although the dataset covers about 18,000 fully profiled organizations, including nearly all publicly listed companies, data quality deteriorates for periods prior to 1999, the year BoardEx began systematic data collection. Consequently, board composition information is more likely to be incomplete for earlier years, particularly for directors who retired before 1999.

Nevertheless, BoardEx remains the most comprehensive dataset available on corporate board composition, capturing about 1.4 million individual executive profiles associated with more than 300,000 organizations and documenting over 10 billion interpersonal connections. I define two individuals as *connected* if they have worked at the same firm in the same city simultaneously, served together on any corporate or non-corporate board, studied the same subject at the same university in the same year, or attended the same church congregation in the same city and year. Membership in mandatory organizations such as bar associations, and broad-based social charities are excluded from this definition. For each director, I construct a *network size* measure variable their total number of unique professional and educational connections. Additionally, a director is considered connected to the board if they share at least one connection with any incumbent board member. Directors are further classified into *insiders*, if they have previous employment with the appointing firm, and *outsiders*, who have no prior affiliation.

A critical limitation is that BoardEx reliably identifies only formal educational and professional networks, while informal or purely social ties are largely unobserved. This limitation has both advantages and drawbacks. On one hand, it mitigates concerns about strategic networking behavior influencing observed connections, thereby reducing potential endogeneity bias. Ambitious individuals indeed attend prestigious schools and switch jobs frequently, indirectly shaping their professional networks, but they are less able to directly manipulate informal connections to secure board positions. On the other hand, omitting informal relationships likely understates the true degree of connectedness among directors.

I complement the BoardEx data with firm-level financial information from CRSP–Compustat, matched using firm identifiers (CUSIP, CIK codes, and tickers) and carefully collapsing duplicates arising from corporate actions such as mergers or ticker changes[1]. This matching procedure yields approximately 1.35 million director–firm–year observations spanning 1990 to 2025, covering 9,377 distinct publicly traded firms and 86,909 individual directors. I specifically focus on roughly 70,000 first-time appointments of ”outsider” directors, defined as directors without prior employment history at the appointing firm. Compustat data is structured around fiscal years, which is convenient since most board tickets are presented at the same time as the fiscal year results, and director appointments are ratified during the annual general meeting of the fiscal year. It is therefore logical to consider that there is a causal relationship between the firm variables for a given fiscal year and director appointments in the following year, typically ratified at the firm’s annual general meeting following the fiscal year. Following Hermalin and Weisbach (1988), I include an array of firm variables such as firm size, firm earnings, leverage, firm performance relative to the industry, size of the board, Market to Book ratio and Tobin’s Q, a measure of firm diversification, and length of CEO tenure.

Before turning to the modeling approach, it is helpful to present descriptive statistics that highlight the complexity behind observed relationships in the data. The average number of preexisting connections to the board per newly appointed outsider director is 1.6 across the full BoardEx sample. Roughly 31% of new appointees have at least one existing connection to the board, and 21% to the incumbent CEO. Within the CRSP–BoardEx matched sample of publicly traded firms, however, newly appointed directors have fewer preexisting connections on average (1.08 connections per appointee), with 26% connected to at least one board member and 15% connected specifically to the CEO. This lower frequency of connections is consistent with the expectation that public firms face stricter oversight than private firms or those financed by private equity.

When restricting the focus to S&P 500 firms, the presence of connections is more pronounced. Newly appointed directors have on average 2.3 preexisting connections to the board, with 40% of appointments connected to at least one board member and 25% that are connected to the CEO. This higher incidence of connections need not indicate causal favoritism. Rather, it may simply reflect that the pool of suitable director candidates for leading public firms is inherently small and that qualified individuals are naturally more likely to have overlapping professional backgrounds.

A potential concern with interpreting these connection counts is mechanical: boards with more members or larger collective networks may be more likely, purely by chance, to appoint a director who happens to know someone already on the board. Table 3.1 partially alleviates this worry by illustrating the quantiles of board connections per appointee for different sizes of boards and board networks. Although larger boards and those with larger collective networks indeed tend to appoint more connected directors, the relationship appears non-linear. In fact, above the median board size or board-network size, the distribution of connected appointees flattens, suggesting that mechanical board size effects alone cannot fully explain the observed connection patterns.

To further investigate these relationships, Figure **??** displays a heatmap of pairwise correlations among key director characteristics, connections, and board attributes. Several insights emerge. First, there is a modest positive correlation (approximately 0.2–0.4) between the log of board network size and both candidate network size and candidate experience. This confirms the intuition that more networked boards tend to attract or identify candidates who themselves have broader professional networks. However,

[1]Firms can change ticker after a merger or an acquisition, can get a different CUSIP when they stop being publicly traded only to become public again later, or following a corporate action.

	72.5%	75%	77.5%	80%	82.5%	85%	87.5%	90%	92.5%	95%	97.5%
All appointees	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	2.00	4.00
Less than median board size	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2.00
Median board size and higher	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	2.00	3.00	5.00
8th decile board size and higher	0.00	0.00	1.00	1.00	1.00	1.00	1.00	2.00	2.00	4.00	7.00
Less than median board network	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	3.00
Median board network and higher	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	2.00	3.00	5.00
8th decile board network and higher	0.00	1.00	1.00	1.00	1.00	1.00	1.00	2.00	2.00	3.00	4.00

Table 3.1: This table displays the quantiles of the number of connections to the board per appointee. The first row describes the quantiles for all appointees, the three next rows present the quantiles for directors appointed to boards of varying size quantiles, and the last three rows present quantiles for directors appointed to boards with varying network size.

notably, candidate network size does not strongly correlate with the number of direct connections to the board itself.

The correlations shown above highlight a key challenge for standard regression analyses. Empirically, boards with larger networks are more likely to appoint directors who have past industry experience, larger professional networks, and direct connections to incumbent directors. Interestingly, candidates with larger personal networks or higher educational credentials (such as MBAs) are not more likely to have direct connections to the appointing board. This pattern runs counter to expectations that well-networked individuals might leverage their personal ties directly to secure board positions. Instead, these correlations likely reflect the underlying structure of candidate pools from which boards recruit: suitable candidates for a given board position are typically drawn from relatively small groups of professionals, who, due to shared professional histories and industry experience, tend to already know incumbent board members.

Boards with larger networks can use their network to tap into broader pools of candidates that disproportionately contain more experienced, more extensively networked, and ultimately better-connected candidates. Such pooling inherently creates a confounding problem in single-stage appointment regressions. Because the choice set is unobserved and often constructed using researcher discretion, standard regressions risk collapsing two conceptually distinct decisions: the consideration decision (who enters the candidate pool/who appears in the search) and the choice decision (who is appointed from that pool). This makes it challenging to discern whether observed ties or candidate characteristics truly drive selection or merely reflect the way candidates are considered in the first place.

To address this problem, I adapt methods from the product-market literature. I explicitly model candidate profiles, aggregating similar candidates into groups defined by observable characteristics. Some candidate profiles naturally have higher baseline probabilities of consideration, analogous to common products in consumer choice models. Importantly, firms with larger board networks can leverage these networks in the consideration stage, giving them access to broader pools of qualified candidates. Explicitly modeling consideration in this manner allows me to separate the structural determinants of candidate availability from boards' genuine appointment preferences.

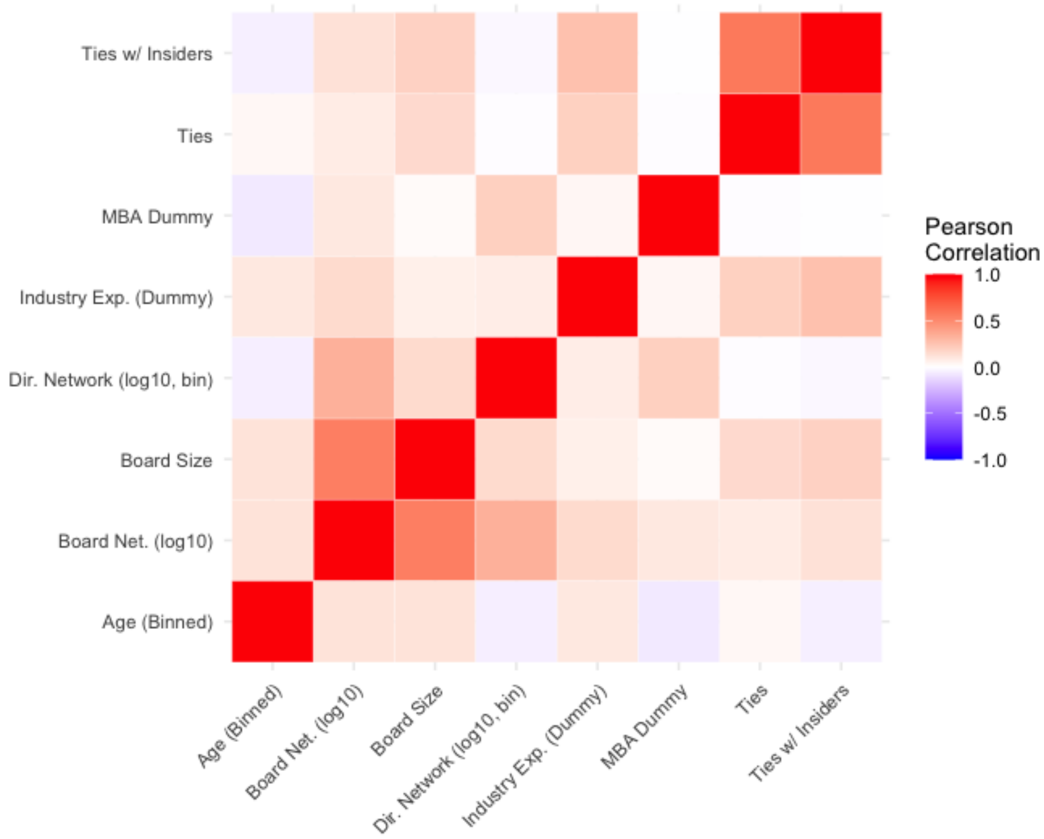

Figure 3.1: Correlation across variables in the sample

3.3 The model

The central challenge in modeling board appointments is that we do not observe the set of candidates each board considers, only the individual ultimately appointed. Most of the literature sidesteps this problem by either ignoring the composition of the choice set or by constructing ad hoc candidate pools, but both approaches risk biasing inference about board preferences.

In this section, I develop a modeling approach that instead aggregates directors into ”profiles”: combinations of observable characteristics such as age, network size, experience, etc. I assume boards choose among all such profiles. However, this aggregation raises a key identification problem: some profiles are inherently rarer, making it hard to distinguish true board preferences from the limited availability of some profiles.

To address this, I proceed in three steps. I first present a baseline multinomial logit model that assumes all profiles are always available, a simplification that conflates preferences and availability. I then extend the model to allow for unobserved heterogeneity across profiles, which can absorb both profile rarity and latent demand, but ultimately does not allow these to be separately identified. Finally, I introduce a consideration set framework that explicitly models the likelihood that a given profile is available to a board, enabling a clean identification of board demand and profile prevalence. At each stage, I make clear what can and cannot be learned from the data, and how the modeling choices address the identification problem posed by unobserved candidate pools.

3.3.1 Setup

Empirically modeling board appointments requires mapping observed director choices back to the underlying preferences of boards. The natural framework is a discrete choice model, where each appointment reflects a board's selection from a set of possible candidates. However, a fundamental complication arises: we never observe the set of candidates that each board actually considered. In the data, we observe only the firm, the appointed director, and both parties' observable characteristics; the pool of alternatives is missing.

Standard empirical approaches often circumvent this issue by collapsing the problem into a binary outcome, such as modeling the probability that a board appoints a "connected" director or that the appointee is an outsider. This implicitly treats "not appointing this director" as the only alternative. While computationally simple, this approach loses critical information: it ignores both the richness of candidate characteristics and the substitutability between different profiles, making it impossible to recover true board preferences or to understand how firm or director characteristics shape appointment patterns. Worse, these models risk severe bias if the unobserved pool of candidates differs systematically across firms or over time.

Alternatively, some studies construct ad hoc choice sets—for example, all directors appointed to firms of similar size in the same region or industry. This strategy is attractive for its practicality, but it can easily misrepresent the true pool of candidates actually available to the board. If the constructed choice set fails to capture some common characteristics of real candidates, or, equivalently, overrepresents extremely unlikely candidates, a characteristic that is actually quite common among real-world candidates (e.g., prior connections to the board or industry experience) might appear rare in the constructed choice set. As a result, models estimated on this basis can dramatically overstate the impact of such characteristics on appointment decisions: if most appointees have, say, a board connection, but this is artificially rare in the reconstructed pool, the estimated "preference" for connections will be upwardly biased. This problem is especially acute for attributes like industry experience or board connections, which are both salient in director selection and difficult to observe comprehensively in the data.

Given these challenges, the goal is to build a structural model that does not require observing the true choice set, but instead makes transparent, data-driven assumptions about how boards select directors. In the next subsections, I introduce an approach that aggregates directors into observable "profiles" and builds stepwise toward a model that can disentangle board preferences from the availability and visibility of different types of candidates.

3.3.2 Choice set construction: Director Profiles as alternatives

The first step is to define the set of alternatives each board can choose from. Rather than treating each individual director as an alternative, I aggregate directors into profiles: combinations of observable characteristics such as age (grouped into brackets), prior board experience, industry background, network size (using the base-10 logarithm, floored), number of board connections, connection to the CEO, and education. Since the number of profiles grows geometrically, I am parsimonious with both the choice of characteristics and their aggregation to avoid a combinatorial explosion in the number of profiles[2].

[2] To ease concerns about arbitrary aggregation cutoff, I ran the estimation with alternative cutoffs and obtained quantitatively similar results.

These profiles serve as the alternatives in all subsequent models: at each appointment event, the board is assumed to choose among the available profiles rather than individuals.

3.3.3 Baseline multinomial logit

Given the profile-based choice set defined above, I begin with a simple multinomial logit framework. Let i denote firms (boards) and j denote potential appointees profiles. For each appointment event, the board is assumed to choose among available profiles based on their observable characteristics.

Formally, let x_j denote the characteristics of profile j, and z_i the characteristics of firm i. Assume the utility to board i from appointing profile j is

$$u_{ij} = V_{ij} + \epsilon_{ij} \tag{3.1}$$

where V_{ij} is the systematic component of utility (a function of observables x_j and z_i), and ϵ_{ij} is an idiosyncratic component of utility, assumed to follow a Gumbel distribution.
I parameterize the systematic utility V_{ij} as a linear function of profile characteristics and firm attributes:

$$V_{ij} = \sum_l x_{jl}\bar{\beta}_l + \sum_{l,r} x_{jl} z_{ir} \beta^o_{lr} \tag{3.2}$$

where $\bar{\beta}_l$ captures average board preferences for profile characteristic l, and β^o_{lr} allows for interactions between firm and profile characteristics.
Under standard assumptions[3] and normalizing the outside option, this yields the familiar multinomial logit choice probability

$$\mathbb{P}_{ij} = \frac{e^{V_{ij}}}{\sum_m e^{V_{im}}} \tag{3.3}$$

This baseline model assumes all profiles are always available to all firms and that unobserved characteristics do not affect appointment decisions. It provides a tractable starting point, but the estimated coefficients may capture both demand for certain characteristics and their underlying availability, as we will show in the next section.

3.3.4 Accounting for director-specific unobserved heterogeneity

The baseline model assumes that all directors with the same observable profile are interchangeable. In reality, however, directors may differ on unobserved dimensions (such as reputation, latent ability, or hidden connections) that influence their probability of being appointed. Further, some profiles might be shared by a larger set of directors. To capture this, I extend the model to allow for unobserved heterogeneity among candidates sharing a given profile.

Let us again denote firms by i, individual directors by k, and let B_j denote the set of directors with observable profile x_j. The utility to board i of appointing director k can be written as:

$$u_{ijk} = V_{ij} + \omega_{ik} + \epsilon_{ijk}$$

[3] Standard assumptions for this kind of models, see McFadden (2001) for a detailed review of the discrete choice literature. Gumbel extreme value standard errors allow for the derivation of the logit specification.

where V_{ij} depends on observed firm and profile characteristics, ω_{ik} captures unobserved attributes of director k, and ϵ_{ijk} is an idiosyncratic shock.

Identification requires additional assumptions on the distribution of ω_{ik}. I impose the restriction that ω_{ik} does not interact with firm characteristics, that is, the unobserved quality of a candidate is valued equally by all boards. Without loss of generality, one can think of ω_{ik} as the intercept of a candidate's quality, while ϵ_{ijk} is the firm-specific idiosyncratic match utility. We can further decompose unobserved heterogeneity as:

$$\omega_{ik} = \bar{\xi}_j + \xi_{jk} \tag{3.4}$$

where $\bar{\xi}_j$ is the average unobserved utility of profile j, and ξ_{jk} is a mean-zero idiosyncratic deviation for director k within profile j.
Assuming that unobserved director characteristics do not interact with firm characteristics, we obtain the following model :

$$u_{ijk} = \sum_l x_{jl}\tilde{\beta}_{il} + \bar{\xi}_j + \xi_{jk} + \epsilon_{ijk}$$

Where I remind the reader that $\tilde{\beta}_{il} = \bar{\beta}_l + \sum_r z_{ir}\beta^o_{lr}$ is the taste of i for characteristic l, and the o superscript stands for observed firm attributes.
This rewrites

$$\begin{aligned} u_{ijk} &= \bar{\xi}_j + \sum_l x_{jl}\bar{\beta}_l + \sum_{lr} x_{jl}z_{ir}\beta^o_{lr} + \xi_{jk} + \epsilon_{ijk} \\ &= V_{ij} + \xi_{jk} + \epsilon_{ijk} \end{aligned}$$

The resulting choice probability for profile j is:

$$\mathbb{P}_{ij} = \frac{\exp(V_{ij} + \Xi_j)}{1 + \sum_m \exp(V_{im} + \Xi_m)} \tag{3.5}$$

where

$$\Xi_j = \ln \sum_{k \in B_j} e^{\xi_{jk}} \tag{3.6}$$

is a profile-specific intercept that absorbs the number of directors sharing a given profile (the cardinality of B_j), since more directors per profile j mechanically increase Ξ_j.

Crucially, in this model, $\bar{\xi}_j$ and Ξ_j are not separately identified. That is, we cannot distinguish whether a profile is rarely appointed because it is inherently unattractive ($\bar{\xi}_j$ is low), or simply because few directors share its characteristics (B_j is small). When running the estimation, the profile-specific intercept absorbs both effects, impossible to separately identify board preferences for a profile from its prevalence in the candidate pool.

In practice, estimation absorbs the profile-level intercepts via fixed effects, which can be decomposed as follows:

$$\delta_j = \Xi_j + \bar{\xi}_j + \sum_l x_{jl}\bar{\beta}_l \tag{3.7}$$

As we do not know the distribution of Ξ_j and $\bar{\xi}_j$, we cannot recover the unbiased value for $\bar{\beta}_l$ for a characteristic l. This limitation is not merely technical: it means that in the baseline model, the estimated effect of an uncommon characteristic on appointments can be biased, attributing to preferences what may in fact reflect simple rarity. This motivates the structured modeling of consideration sets in the next section, which aims to separate board demand from profile availability.

3.3.5 Choice Set Consideration

The previous model cannot disentangle whether a director profile is rarely appointed because boards disfavor its characteristics or simply because such profiles are unlikely to be present in the set of candidates a board actually considers. Further, it is most likely that different firms face different choice sets: finding a good candidate is a difficult process, and not all options are available to every single firm. To address this limitation, I introduce a consideration set framework that makes explicit the process by which profiles enter a board's candidate pool.

In a consideration set model, we jointly estimate the probability of one option to be present in the choice set and the probability of this option to be chosen. This requires that a characteristic that shifts the choice set does not enter the utility derived from a choice.

The model assumes that board i appoints a director in two stages. First, each potential profile j is either considered or not, with probability ϕ_{ij} that depends on both board and profile characteristics. Then, conditional on being considered, the profile that maximises the firm's utility is selected for appointment.

Formally, let us define the consideration function ϕ_{ij}, defining the probability of profile j being considered by firm i.

$$\phi_{ij} = \frac{e^{\gamma_{ij}}}{1 + e^{\gamma_{ij}}}$$

Where γ_{ij} is a function of firm characteristics and director profile observables. For example, γ_{ij} can include both profile-level variables (e.g., network size, prior experience) and board-level characteristics (e.g., board size, board network), or their interactions.
Crucially, identification relies on the assumption that certain variables (in our case, the size of the board's network) enter only the consideration equation, not the final utility, which provides the necessary exclusion restriction for separate identification of consideration and choice.

Let C denote a potential set of considered profiles for board i. The probability that C is the actual consideration set considered by firm i is given by

$$\pi_i^C = \prod_{j \in C} \phi_{ij} \prod_{k \notin C} (1 - \phi_{ik})$$

Conditional on C, the probability that board i appoints profile $j \in C$ follows the multinomial logit form:

$$\mathbb{P}_{ij}(x_j, z_i | C) = \frac{e^{V_{ij}}}{\sum_{m \in C} e^{V_{im}}}$$

This yields the formal choice probabilities:

$$p_{ij} = \sum_C \prod_{l \in C} \phi_{il} \prod_{k \notin C} (1 - \phi_{ik}) \mathbb{P}_{ij}(x_j, z_i | C) \tag{3.8}$$

That is, the probability that j is considered (as part of some C), multiplied by the probability it is chosen conditional on being in the set.

Because of the increased computational complexity of this model[4], it must be estimated via simulation, as described in Goeree (2008) and Abaluck and Adams-Prassl (2021). Details of the estimation procedure are provided in the appendix 3.B.

As stated above, a key identification assumption is that some board-level variables (e.g., the board's network size) affect only consideration, not utility. This restriction is necessary to separately identify consideration from choice, but it is ultimately a structural assumption and should be interpreted as such. I allow the choice set to be a function of the director's experience, the director's network, the director's preexisting relationship with the board, and the size of the board's network. The inherent logic is that profiles that are more connected with a larger network and a more relevant job experience should be rarer, while a board with a larger network should be more likely to access rare potential candidates.

This captures two fundamentally different effects. The first is, in essence, purely mechanical: A board with a larger network is more likely to have pre-existing connections with a randomly chosen appointee. Therefore, candidates with pre-existing relationships are more likely to be "considered" if the board has a larger network. The second effect stems from the proposed board recruitment mechanism. Anecdotal evidence[5] shows that directors are using their network to search for suitable candidates. If we follow this line of thought, rare profiles are relatively more likely to be considered by firms with large networks than by firms with small board networks. Consequently, the estimated positive consideration coefficients for the board network parameters show that boards do indeed use their networks to find suitable applicants.

3.4 Estimation Procedure and Identification

3.4.1 Overview of the estimation procedure

I progressively estimate three models: (1) a baseline multinomial logit model, (2) a model incorporating unobserved profile heterogeneity, and (3) a consideration set model explicitly modeling the candidate pool formation process.

In each model, the estimation approach centers around maximizing the likelihood function constructed from observed appointments and candidate profiles. To ensure the tractability of the estimation, given the choice set of a firm, I define the outside option as appointing an insider director. That is, an individual who is already employed within the firm. Companies typically seek outsider appointments, candidates without prior employment relationships with the firm, to satisfy independence criteria required by regulators, investors, and market expectations. Thus, appointing an insider serves as a meaningful but relatively unattractive fallback option when the search fails.

Arguably, another suitable outside option would be to renew the mandate of a currently sitting director. However, the board recruitment process seems not to be driven by such concerns: the decision to replace a director is often taken months before a suitable candidate is found, and the search process is usually lengthy and quite costly for the firm. Hence, in practice, renewing incumbent mandates seldom represents the default alternative when no suitable candidate is found.

I follow Keane and Wasi (????) and approximate the choice set by randomly sampling 20 profiles for each firm when estimating the baseline model and the unobserved characteristics model.
I estimate a model by maximising the logarithm of its likelihood function. While this is quite straightfor-

[4] The sum in equation 3.8 is over 2^J possible sets.

[5] See Cai et al. (2021)

ward for the base model, the unobserved characteristics model and the consideration set model deserve some comments.

3.4.2 Unobserved Characteristics

In the unobserved characteristics model, I follow the methodology proposed by BLP[6], embedding a nested-loop estimation algorithm that incorporates unobserved characteristics into the profile-specific intercepts (mean utilities, denoted by δ_j). Formally, let us define the *observed* mean utility from good j, δ_j as

$$\delta_j = \sum_l x_{jl}\bar{\beta}_l + \bar{\xi}_j + \Xi_j$$

where x_{jl} denotes observable characteristics of profile j, $\bar{\beta}_l$ represents coefficients for these characteristics, and $\Xi_j + \bar{\xi}_j$ captures rarity and the profile-specific unobserved characteristics.

Crucially, the identification of this model requires assumptions on the distribution of unobserved profile-specific utilities. In particular, without additional assumptions, the coefficients on observable profile characteristics ($\bar{\beta}_l$) cannot be separately identified from the profile-specific intercepts ($\Xi_j + \bar{\xi}_j$)[7]. However, interaction coefficients between firm-level attributes and candidate characteristics (β^o) remain separately identifiable, which provides a good sanity check for the standard errors of the baseline model, as not accounting for unobservables biases standard errors and overestimates precision (Murdock, 2006).

implement this estimation, I employ a nested-loop approach. I follow Murdock (2006) and I estimate the log-likelihood by maximizing the log-likelihood[8], At each iteration of this outer loop, the algorithm takes as given the mean utilities δ_j provided by the inner loop, which estimates the mean utilities via a contraction mapping algorithm, known as the BLP contraction. Given observed market shares (s_j) and predicted market shares ($\hat{s}_j$), the algorithm iteratively updates mean utilities according to:

$$\delta_t = \delta_{t-1} + \ln s_j - ln(\hat{s}_j|\delta_{t-1})$$

As the analytical gradient is misspecified (it cannot take into account the impact of the change of parameters on the coefficients δ), convergence is slow, but this algorithm is still more stable and faster than estimating the δ together with the β using gradient methods[9].

3.4.3 Consideration Set Model

As explained in section 3.3.5, the estimation procedure relies on simulation and is described in detail in the appendix. Formally, the estimation proceeds in two stages. For each firm, I first generate R simulated choice sets using antithetic acceleration to reduce simulation variance and computational burden. For each simulated choice set, I calculate conditional choice probabilities and then average these probabilities across simulations to obtain stable estimates of unconditional choice probabilities. Importance sampling ensures that simulated likelihood values remain stable and smoothly converge to the true maximum.

[6] Berry et al. (1995)

[7] Assuming $\mathbb{E}(\Xi_j) + \bar{\xi}_j = 0$, we could recover $\bar{\beta}$ with a simple OLS regression of δ_j on characteristics. However, this would be quite unreasonable, as $E(\Xi_j)$ is proportional to the cardinality of B_j as we discussed earlier.

[8] Specifically, the Berndt–Hall–Hall–Hausman algorithm.

[9] As the δ are alternative specific coefficients, maximum likelihood is notably prone to dramatic overfitting when they are estimated through gradient methods. See Bierlaire et al. (1997) for a discussion.

To simulate firm i's choice set, I first fix $R/2$ draws of uniform random variables over the available profiles $j \in \{1, ..., J\}$. I then generate their $R/2$ antithetic covariates[10] to obtain R draws of J uniform random variables. Using parameter values, I compute ϕ_{ij} for each j, and compare it to the corresponding uniform draw. If the value of the probability is higher than the draw, it is in the choice set. By repeating this process for each profile for each of the R draws, I obtain R choice sets for each firm.

Once the choice set are determined, I estimate the choice probabilities for each firm-draw, conditional on choice set and parameter values. Importantly, choice probabilities are computed using importance sampling with reference to the initial choice set, so as to ensure convergence of the estimates[11]. Averaging the likelihood functions resulting from these choice probabilities yields the simulated likelihood, which can then be maximised. I use the Berndt–Hall–Hall–Hausman algorithm, but I compute the final Hessian numerically so that I can allow for potential heteroskedasticity[12].

Identification in this model relies on an exclusion restriction: the size of the board's network affects only the probability of consideration but does not directly influence the conditional choice decision. While this assumption is economically justifiable – board networks should primarily affect candidate search rather than intrinsic preferences of the board – it remains a strong assumption.

3.5 Results

3.5.1 Firm and director controls

Before delving into the main findings, it is essential to precisely define and contextualize the firm-level and director-level control variables used throughout the analysis. Table 3.2 provides a thorough description of these variables. Director characteristics include attributes such as age, educational credentials (MBA, JD, graduate degrees), network size, and direct prior industry experience, all of which could influence board appointment decisions. Firm controls encompass governance and performance indicators, including board size, firm size (log assets), leverage, Tobin's Q, ROA relative to industry, whether a new CEO has been recently appointed, and the number of industries the firm operates in.Firm controls are fundamentals that are likely to influence the marginal value of connections, networks, and experience for board recruitment decisions.

3.5.2 Terminology

In this model, firm characteristics are interacted with candidate (profile) characteristics, which makes economic interpretation of the results difficult, both in terms of magnitude and economic significance. In order to streamline the discussion, in the following I will refer to the mean effect of a variable and to the standard effect of a variable. The mean effect of variable l is be defined as

$$\text{MEf}_l = \bar{\beta}_l + \sum_r \mathbb{E}(z_{ir})\beta^o_{lr}$$

[10] Antithetic acceleration drastically reduces the variance from simulation and is less costly in terms of computer memory. See Geweke (1988).

[11] Indeed, a change in choice set could induce a very large change in choice probabilities, which would induce discontinuities in the log-likelihood. A discontinuous log-likelihood might not converge to its maximum using standard optimisation procedures.

[12] The BHHH approximated Hessian is equal to the 'meat' of the Huber-White sandwich estimator, which yields mathematical equivalence between the HW covariance variance matrix and the BHHH covariance matrix.

Table 3.2: Variables description

Director characteristic	Aggregated Values
Age	- 40, 40-50, 50-60, 60-70, 70 +
Network size (log 10)	0, 1, 2, 3, 4
Contacts in the board	0, 1, 2, 4
Bachelor	0,1
Graduate diploma (MD, PhD, Masters)	0,1
Juris Doctorate	0,1
MBA	0,1
Industry experience (SIC code at the 3 digit level)	0,1

Firm Characteristic	Description
Board Size	Size of the board
Size	Logarithm of the Asset holdings
ROA	Deviation from the firm's industry ROA
Leverage	Leverage ratio
Tobin's Q	Tobin's Q ratio
Supervisory director	Non-executive appointment
Industries	Number of 3 digit SIC the company is spanning
NEWCEO	New CEO appointed in the last 3 years
Board Network	log of the board's network

And represents the effect of an increase of one unit in the variable l on the choice utility of the average firm in the sample.
Similarly, the scaled standard deviation of variable l given firm characteristic r is defined as

$$\text{StEf}_{lr} = \sigma(z_{ir})\beta^{o}_{lr}$$

And represents the effect of a standard deviation of firm characteristic r on the choice utility provided by variable l.
This terminology will help quantify the economic magnitude of effects. When the mean effect of characteristic l is negative, an increase in characteristic l will decrease the probability that a given profile is chosen. Further, a very small average standard deviation relative to the mean effect can be interpreted as an interaction coefficient being economically insignificant, as the variation found in the data will have little impact on the magnitude and directionality of the estimate.
Finally, I will make the distinction between a networked and a connected director. A networked director has a large network of interpersonal relationships observable in the dataset, acquired through past work experiences or through her studies. A connected director has a pre-existing relationship (connection) with at least one member of the board.

3.5.3 Hypotheses and Interpretive Framework

I explicitly state and clarify the following key hypotheses, along with their implications for expected patterns in the data:

H1 (Cronyism): If board appointments primarily reflect cronyistic behavior, we expect firms with poor performance metrics (low ROA, high leverage), weaker governance, and potentially entrenched management structures (large size, high Q indicating overvaluation) to systematically favor directors who have pre-existing relationships ("connections") with current board members.

H2 (Screening): If boards utilize the candidates' professional networks as a screening device for candidate quality, we expect larger candidate networks to significantly increase the probability of appointment, particularly for supervisory director roles where performance evaluation is inherently more challenging as the contribution to a board is diluted. Additionally, we might expect personal connections (pre-existing relationships) to become relatively less important for multi-industry or very large firms (since diverse or specialized recruitment needs reduce the effectiveness of personal connections as screening devices), and relatively more important in firms with stronger financial performance (higher ROA), where quality screening may be of paramount importance.

H3 (Coordination): If connected directors are helpful to ensure coordination and easier board decision making, firms undergoing management or organizational transitions (such as the appointment of a new CEO) should preferentially select directors who already have direct ties to the existing board. Additionally, we would expect executive (rather than supervisory) directors to be more likely to be connected since they have a central role in day-to-day decision-making processes.

H4 (Expertise): Boards seeking specific expertise should systematically prefer candidates with relevant industry experience, especially in periods of uncertainty or management transition (new CEO). The demand for industry-specific knowledge is also expected to be stronger for supervisory directors, who offer strategic oversight, rather than executive directors (who might have specialized roles such as CFO or CTO). However, this preference for expertise should be less pronounced for multi-industry firms or larger firms, where specialized industry knowledge might be diluted or less critically valued.

In the following, I discuss in detail the empirical results obtained from the progressive estimation of the three models: the baseline model, the model incorporating unobserved characteristics, and the final model explicitly modeling consideration sets. Each step tests the hypotheses outlined above and progressively addresses biases in previous estimations.

3.5.4 Baseline model results

The baseline model estimation discussion focuses on two variables of interest: the number of pre-existing relationships between the appointee and the current board, and the overall size of the appointee's professional network.

The baseline estimation in table ?? provide initial evidence consistent with the cronyism hypothesis (H1). Larger firms, more leveraged firms, those with lower profitability (ROA), and firms with higher Tobin's Q ratios all exhibit a significantly higher likelihood of appointing directors with pre-existing relationships with current board members. Such a pattern is consistent with entrenched governance or nepotistic decision-making. Yet, the baseline model also suggests that coordination (H3) and screening (H2) might be at play. Specifically, the presence of a newly appointed CEO strongly correlates with the recruitment of connected directors, which could suggest an intent to exploit personal connections to foster smoother collaboration and information flow. Likewise, executive director appointments are more likely to involve candidates with board connections, which supports the notion of internal coordination benefits.

Table 3.3: Baseline Model: Impact of Pre-existing Relationships.
This table presents the results from the baseline model estimation. The dependent variable is the likelihood that a firm appoints a director with the observed appointee's profile. The first column reports the raw estimate for the effect of one additional pre-existing relationship, interacted with the indicated firm characteristic, on u_{ij}. The second column shows the effect of a one standard deviation change in the firm characteristic (estimate × standard deviation). The third column reports the t-statistic, and the fourth column indicates the significance level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).
The row labeled "Mean" reports the average effect of one additional pre-existing relationship, evaluated at the mean of the relevant firm characteristics. In this specification, the impact of an additional pre-existing relationship is negative.

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	0.05	0.15	25.82	***
ROA	-0.13	-0.03	-4.93	***
Size	0.07	0.15	20.19	***
leverage	0.01	0.01	2.77	***
Q	0.08	0.08	12.38	***
Industries	-0.08	-0.06	-11.82	***
NEWCEO	0.18	0.09	17.23	***
Board Network	0.07	0.10	13.37	***
Supervisory Director	-0.10	-0.04	-6.78	***
Intercept	-2.67		-66.83	***
Mean effect of a relationship	-1.272695			
Number of observations	69843			
Log-Likelihood	-130696.2	Pseudo R^2	0.39229	

Finally, there are three relationships that I posit to be purely mechanical. Firms with a larger board and boards with a larger network are more likely to appoint connected directors because the probability of a director being connected to a member of the board is mechanically higher, and firms operating in fewer industries are more likely to appoint a connected directors as their candidate pool is likely concentrated among a smaller group of industry specialists. This mechanical explanation is supported by additional results in Table 3.14, which show that firms spanning few industrieshave a higher propensity to appoint directors with relevant past industry experience.

Results presented in Table 3.4 indicate that firms recruiting directors with larger networks are bigger, less leveraged, have a slightly lower Tobin's Q than average and are more likely to have a recently appointed CEO, which strongly supports the screening hypothesis (H2). The magnitude and statistical significance of the coefficients imply that networks may serve as credible signals of quality or reliability. Supervisory directors, who play strategic oversight roles, particularly benefit from larger networks, which might reflect the inherently greater difficulty in evaluating their competence relative to executive directors and the greater need to rely on screening through entworks.

Finally, I have to discuss the mean effect of pre-existing relationship and of the size appointee's network. In this specification, an additional pre-existing relationship with a board member is, on average, associated with a lower probability of appointment. Conversely, having a larger overall network will make an appointee more likely to be appointed to the board. Interpretations at this stage must be cautious[13], yet this hints at a mis-identification of the impact of pre-existing relationships in previous literature. Indeed, directors with a larger network are mechanically more likely to have pre-existing relationships with members of the board, but have a higher likelihood of appointment because of the director referral

[13]As discussed above, biases are mostly related to the composition of the choice set given the aggregation procedure. Profiles with a large number of pre-existing relationships are likely to be uncommon, whereas they represent a large number of the aggregated profiles.

Table 3.4: Baseline Model: Impact of Appointee's Network.
This table presents the results from the baseline model estimation. The dependent variable is the likelihood that a firm appoints a director with the observed appointee's profile. The first column reports the raw estimate for the effect of an increase in the magnitude of the appointee's network, interacted with the indicated firm characteristic, on u_{ij}. The second column displays the effect of a one standard deviation change in the firm characteristic (estimate × standard deviation). The third column reports the t-statistic, and the fourth column indicates the significance level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).
The row labeled "Mean" reports the average effect of an increase in network size, evaluated at the mean of the relevant firm characteristics. In this specification, the impact of a larger network is positive.

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	-0.02	-0.08	-8.74	***
ROA	-0.04	-0.01	-1.24	
Size	0.06	0.14	14.25	***
leverage	-0.02	-0.05	-6.07	***
Q	-0.02	-0.02	-2.17	**
Industries	0.01	0.01	1.38	
NEWCEO	0.06	0.03	3.85	***
Board Network	0.19	0.28	30.37	***
Supervisory Director	0.13	0.05	5.58	***
Intercept	-1.81		-34.41	***
Mean effect of log_{10} network	0.2524255			
Number of observations	69843			
Log-Likelihood	-130696.2	Pseudo R^2	0.3922	

process described in Fahlenbrach et al. (2018) and not particularly because of direct connections to the board. We will see in the following that this intuition is confirmed in the choice set consideration model.

3.5.5 Unobserved Characteristics model

Table 3.5: Unobserved Characteristics Model: Impact of Pre-Existing Relationships.
This table presents the results from the specification with mean utilities accounting for unobserved characteristics, such as the rarity of a director's profile. The dependent variable is the likelihood that a firm appoints a director with the observed appointee's profile. The first column reports the raw estimate for the effect of one additional pre-existing relationship, interacted with the indicated firm characteristic, on u_{ij}. The second column shows the effect of a one standard deviation change in the firm characteristic (estimate × standard deviation). The third column reports the t-statistic, and the fourth column indicates the significance level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	0.03	0.10	8.02	***
ROA	-0.08	-0.02	-1.67	*
Size	0.02	0.04	2.45	**
leverage	0.01	0.02	1.40	
Q	-0.01	-0.01	-1.26	
Industries	-0.02	-0.02	-1.50	
NEWCEO	0.06	0.03	2.93	***
Board Network	-0.09	-0.13	-14.77	***
Supervisory Director	-0.09	-0.03	-3.65	***
Number of observations	69843			
Log-Likelihood	-17748.91	Pseudo R^2	0.91747	

Estimates of the unobserved characteristics model are presented in Tables 3.5 and 3.6. Incorporating unobserved profile-level heterogeneity significantly refines our understanding. After controlling for the inherent rarity and latent appeal of specific profiles in Table 3.5, the previously strong evidence for cronyism (H1) substantially weakens. Specifically, the association between poor firm performance

Table 3.6: Unobserved Characteristics Model: Impact of Appointee's Network.
This table presents the results from the specification with mean utilities accounting for unobserved characteristics, such as the rarity of a director's profile. The dependent variable is the likelihood that a firm appoints a director with the observed appointee's profile. The first column reports the raw estimate for the effect of an increase in the magnitude of the appointee's network, interacted with the indicated firm characteristic, on u_{ij}. The second column shows the effect of a one standard deviation change in the firm characteristic (estimate × standard deviation). The third column reports the t-statistic, and the fourth column indicates the significance level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	0.00	0.00	0.13	
ROA	-0.15	-0.04	-1.25	
Size	0.05	0.12	3.03	***
leverage	-0.02	-0.06	-1.90	*
Q	-0.11	-0.11	-4.33	***
IndustriesSpanning	0.03	0.03	0.98	
NEWCEO	0.05	0.03	0.94	
logBoardNetwork	-0.01	-0.01	-0.48	
SupervisoryDirector	-0.01	-0.00	-0.22	
Number of observations	69843			
Log-Likelihood	-17748.91	Pseudo R^2	0.91747	

(low ROA, high leverage) and the appointment of connected directors markedly diminishes, with some coefficients becoming statistically insignificant. However, larger boards and firms with newly appointed CEOs remain significantly more likely to appoint directors with pre-existing relationships, preserving partial support for the coordination hypothesis (H3).

For networked directors, Table 3.6 shows findings that are largely consistent with the screening hypothesis (H2). Directors with larger networks continue to attract appointments in large, relatively less leveraged firms. Notably, the importance of networks appears robust, though interactions lose some statistical significance, perhaps due to controlling for unobserved profile-level quality effects. These results strengthen the argument that board recruitment decisions strongly reflect a desire to use professional networks as a screening mechanism, distinct from mere cronyistic motivations.

As I stay agnostic regarding the distribution of mean utilities, I cannot recover the intercept of the estimates, and I therefore cannot compute the mean effect of a change in profile characteristics with this specification.

3.5.6 Consideration Set Model

The consideration set model explicitly addresses the candidate availability problem, providing the clearest and most nuanced assessment of the hypotheses. Parameter estimates in the consideration set model are to be taken as the value of the estimate *conditional on the profile being considered*. The full results including consideration parameters estimates are reported in table 3.16 of the appendix.

First, evidence decisively rejects the cronyism hypothesis (H1). Once the likelihood of candidate consideration is explicitly modeled in Table **??**, candidates with direct board connections are no longer systematically favored by poorly performing or weakly governed firms. The mean effect of connections is actually negative, indicating that, conditional on consideration, the existence of a relationship with a member of the board might be detrimental to the candidate.. This finding strongly suggests that previous evidence of cronyism was driven primarily by biases induced by choice set selection, rather than genuine

Table 3.7: Consideration Set Model: Impact of Pre-Existing Relationships.
This table presents the results from the estimation of the choice set consideration specification. The dependent variable is the likelihood that a firm appoints a director with the observed appointee's profile. The first column reports the raw estimate for the impact of one additional pre-existing relationship, interacted with the indicated firm characteristic, on u_{ij}. The second column shows the effect of a one standard deviation change in the firm characteristic (estimate × standard deviation). The third column reports the t-statistic, and the fourth column indicates the significance level ($^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$).
The row labeled "Mean" reports the average effect of one additional pre-existing relationship, evaluated at the mean of the relevant firm characteristics. In this specification, the estimated impact of an additional pre-existing relationship is negative.

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	0.05	0.15	21.45	***
ROA	-0.07	-0.017	-1.87	*
Size	-0.01	-0.011	-1.29	
leverage	0.02	0.04	6.73	***
Q	0.07	0.01	5.84	***
Industries	-0.14	-0.11	-18.37	***
NEWCEO	0.08	0.037	5.64	***
Supervisory Director	-0.16	-0.055	-8.61	***
Intercept	-1.76		-53.84	***
Mean effect of a relationship	-1.533248			
Number of observations	69843			
Log-Likelihood	-68523.18			

nepotistic preferences. Further, most of the significant interaction coefficients are arguably mechanical. A larger board will have a higher probability to be connected to a random candidate *ceteris paribus*, and it is probable that larger firms and firms spanning few industries recruit from a smaller pool of interconnected candidates[14].

Second, the screening hypothesis (H2) emerges as the dominant narrative: as described in Fahlenbrach et al. (2018), director candidates would be recruited through a referral process. The network size of directors (Table 3.8) has the largest positive impact on appointment probabilities across all specifications. Firms systematically prefer well-networked candidates, particularly for supervisory director roles, which underscores networks as critical signals of quality in contexts where direct performance metrics are unavailable. Moreover, in firms that span multiple industries or have larger, more diverse boards, direct screening via pre-existing personal connections becomes less effective. This is likely because no single director's connections or competencies fully align with the broader range of needs or expertise required in such complex organizations. In these settings, personal connections with existing board members are less likely to provide a strong or relevant quality signal for the role at hand. However, second-order screening—where directors rely on broader referrals from their extended professional networks—remains valuable.

Third, the expertise hypothesis (H4) finds robust and clear support in the consideration set model. Table 3.9 shows that relevant industry experience is highly valued, particularly during CEO transitions or for supervisory roles, precisely when strategic oversight and informed advisors are most crucial. Even though the mean effect was negative in the baseline model, it is now strongly positive. The magnitude of these effects is economically substantial and strongly statistically significant. Larger or multi-industry firms down-weight the importance of specific industry experience, consistent with expectations that specific expertise requirements decrease as firm complexity or industry diversity increases.

[14] Suitable candidates to the board of a S&P500 firm are presumably few, and single industry firms might be interested in specialists of the industry.

Table 3.8: Consideration Set Model: Impact of Appointee's Network

This table presents the results from the estimation of the choice set consideration specification. The dependent variable is the likelihood that a firm appoints a director with the observed appointee's profile. The first column reports the raw estimate for the effect of the director's network magnitude, interacted with the indicated firm characteristic, on u_{ij}. The second column displays the effect of a one standard deviation change in the firm characteristic (estimate × standard deviation). The third column reports the t-statistic, and the fourth column denotes the significance level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).
The row labeled "Mean" reports the average effect of an increase in the director's network magnitude, evaluated at the mean of the relevant firm characteristics. In this specification, the estimated impact of a larger director network is negative.

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	-0.09	-0.29	-18.68	***
ROA	0.15	0.0366	2.14	**
Size	-0.01	-0.032	-1.74	*
leverage	-0.01	-0.015	-1.19	
Q	-0.05	-0.049	-2.53	**
Industries	0.05	0.042	3.26	***
NEWCEO	0.02	0.00	0.54	
Supervisory Director	0.92	0.33	24.16	***
Intercept	2.84		43.49	***
Mean effect of log_{10} network	2.82782			
Number of observations	69843			
Log-Likelihood	-68523.18			

Finally, while the coordination hypothesis (H3) retains some relevance (new CEO firms still favor connected directors, albeit modestly), the magnitude and significance of these effects pale compared to the screening and expertise hypotheses. Thus, while facilitating internal coordination might still matter, its empirical relevance appears limited relative to screening and expertise.

3.5.7 Summary of empirical findings

By explicitly modeling candidate consideration, the final model provides definitive evidence that previous literature likely overstated the role of cronyism in board appointments. Instead, boards seem primarily driven by considerations of candidate quality (screening) and strategic capability (expertise), using professional networks and industry-specific knowledge as credible signals to resolve informational asymmetries inherent in director appointments.

These findings have critical implications for governance policy and future research, emphasizing the importance of clearly distinguishing candidate availability from board preferences in empirical modeling of corporate appointments.

3.6 Appointment to committees

3.6.1 Board committees

Committee appointments offer a particularly useful robustness check because, contrary to board appointments, the full set of eligible candidates is explicitly observed. To be appointed to a board committee, one needs to be a director, making it possible to directly test the validity of the main hypotheses (H1–H4) without ambiguity from choice set mis-specification.

Two committees are especially relevant: the audit committee, which oversees the integrity of financial disclosures, and the compensation committee, which determines executive pay and incentive structures.

Table 3.9: Consideration Set Model: Impact of Past Industry Experience
This table presents the results from the estimation of the choice set consideration specification. The dependent variable is the likelihood that a firm appoints a director with the observed appointee's profile. The first column reports the raw estimate for the effect of past industry experience at the 3-digit SIC level, interacted with the indicated firm characteristic, on u_{ij}. The second column displays the effect of a one standard deviation change in the firm characteristic (estimate × standard deviation). The third column reports the t-statistic, and the fourth column denotes the significance level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).
The table row labeled "Mean" reports the average effect of industry experience, evaluated at the mean of the relevant firm characteristics. In this specification, the impact of industry experience on the odds ratio is very large.

Firm Variable	Estimate	Std Effect	tstat	
boardsize	-0.07	-0.23	-5.93	***
ROA	-0.16	-0.039	-0.74	
Size	-0.07	-0.17	-3.33	***
leverage	-0.03	-0.085	-2.32	**
Q	0.17	0.162	1.73	*
Industries	-0.08	-0.061	-2.26	**
NEWCEO	0.56	0.27	7.14	***
Supervisory Director	0.83	0.30	7.28	***
Intercept	5.71		25.52	***
Mean effect of industry experience	5.682979			
Number of observations	69843			
Log-Likelihood	-68523.18			

Given their crucial governance functions, these committees provide a transparent context for evaluating whether the Cronyism (H1), Screening (H2), Coordination (H3) and Expertise (H4) hypotheses.

I run the estimation over all observed appointments of directors to committees in the Boardex database. I exclude observations where I cannot observe the complete choice set at the time of the appointment (such as when a committee member has been appointed before the firm entered the dataset) or when the CEO is the appointee (as I consider such committee appointment to have a different nature). Accordingly, the choice set is composed of all directors sitting on the board, excluding the CEO. The outside option is to appoint a director who was an insider at the time of recruitment.

3.6.2 Results

Strikingly, results are extremely similar for compensation committee and audit committee appointments, despite a minority of directors cumulating appointments in both committees. Empirical results strongly align with the screening hypothesis and decisively reject the cronyism and coordination hypotheses. Strikingly, pre-existing relationships have a negligible impact on the likelihood of appointment to either audit or compensation committees. Instead, the primary determinants of committee appointments are supervisory roles, relevant expertise (an MBA markedly increases the likelihood of sitting on the audit committee), and, notably, the size of a director's professional network at the time of nomination.

Moreover, there are diminishing returns to the size of a candidate's network: the influence of a candidate's network on their appointment probability decreases as the board's overall network size grows. On the other hand, a large board network makes it more likely overall to appoint an outsider to a committee rather than an insider. This suggests that boards with larger networks can rely on their own network to gauge the quality of an appointee. Finally, while large firms place less value on individual pre-existing connections, they attach greater importance to the candidate's overall network size.

In sum, the explicit observation of the choice set for committee appointments reinforces and sharpens

Table 3.10: Audit Committee Appointments
This table displays the result of the estimation for the committee appointments. The dependent variable is the likelihood for a board to appoint a given director to the Audit Committee. The choice set is composed of all members of the board apart from the CEO. The first column displays the estimates, the second column displays the t-statistic and the fourth column displays the significance level (*=10%, **=5%, ***=1%)
The Gender variable takes a value of 1 for men and 0 for women.

	Estimate	t-stat	p-value
Board size-Intercept	-0.48	-30.38	***
Size-Intercept	0.08	2.91	***
ROA-Intercept	0.30	1.61	
Board Network-Intercept	0.98	20.55	***
Leverage-Intercept	0.10	4.74	***
Intercept-Intercept	-9.24	-23.84	***
Board Size-Contacts at nomination	0.03	16.16	***
Size-Contacts at nomination	-0.03	-5.73	***
ROA-Contacts at nomination	0.06	1.46	
Board Network-Contacts at nomination	0.01	0.65	
Leverage-Contacts at nomination	0.00	0.59	
Intercept-Contacts at nomination	-0.11	-1.35	
Mean:	0.38		
Board Size-NetworkSize	0.07	19.49	***
Size-NetworkSize	0.04	5.34	***
ROA-NetworkSize	-0.15	-2.58	***
Board Network-NetworkSize	-0.48	-30.95	***
Leverage-NetworkSize	-0.02	-4.03	***
Intercept-NetworkSize	3.79	29.51	***
Mean:	0.0034		
Gender	-0.34	-17.60	***
Age	-0.01	-8.79	***
Supervisory	5.05	58.75	***
Bachelor	0.26	13.17	***
MBA	0.21	14.08	***
Graduate Degree	-0.38	-24.91	***
Experience	-0.28	-13.66	***
N observations	34941	Log-Likelihood	-50492

the overall evidence: networks matter primarily as screening tools, not as vehicles for nepotism or coordination.

3.7 Concluding remarks

3.7.1 Summary: What matters for director appointments?

The results presented throughout this paper provide strong support for the screening hypothesis and decisively less support for cronyism and coordination theories. Directors' pre-existing personal relationships with current board members have negligible effects on appointment probabilities once the analysis explicitly accounts for endogenous choice set consideration. Instead, relevant experience, supervisory roles, and network size significantly increase a director's likelihood of appointment.

As in the previous literature, there is some evidence suggesting that some firms are hiring connected directors because of nepotism or coordination concerns. Nonetheless, the magnitude of these estimates is small, and this seems to be of second order importance. Namely, firms hiring connected directors seem to have a slightly lower adjusted ROA, a slightly higher leverage, a higher Tobin's Q and are larger on average. They also tend to have a recently appointed CEO[15].

Overall, having a pre-existing relationship with a member of the board seems to be unfavourable to the potential appointee. Indeed, market forces may strongly discourage explicit cronyism, as suggested by negative shareholder reactions documented in prior studies (Cai et al., 2021). Additionally, the structural incentives for cronyism might themselves be limited: helping a relationship to become a director to another board expands the joint network of the appointed director and the refereeing director, while appointing them to the referee's own board does not expand their joint network (Fahlenbrach et al., 2018). On the other hand, the size of a director's network and relevant past job experience have a large positive impact on her probability of appointment. The evidence, therefore, broadly supports the idea of an efficient market for directors where screening and referrals dominate.

3.7.2 Summary: Why consideration sets?

While discrete choice models are relatively robust to some forms of misspecification, they are highly sensitive to the composition of the underlying choice set, especially when the true choice set is not observed. In the context of director and CEO appointments, this poses a major challenge: the set of candidates considered for board seats is rarely, if ever, directly observable, so researchers must construct the choice set ad hoc. This inevitably risks bias. For example, if candidates with rare characteristics, such as large networks or specific experience, are either over- or under-represented in the constructed choice set, estimates of their impact will be systematically distorted. As a result, traditional models can easily underestimate the true value of networks and experience in appointments.

I contend that consideration set models are a satisfying solution to this problem. Consideration set models offer a practical and theoretically appealing solution to this problem. By explicitly modeling both which candidates are considered, these models are able to correct for the bias introduced by misspecified choice sets, and deliver point-identified, more credible estimates. The main cost is computational[16], but this is increasingly manageable with modern computing resources. In my results, the use of consideration set models leads to intuitive bias corrections.

An additional check on the credibility of the approach comes from the analysis of committee appointments, where the choice set is directly observed: all directors (except the CEO) are eligible, eliminating ambiguity about which candidates could be chosen. Strikingly, the results from committee appointments closely mirror those from the board appointment analysis: the influence of pre-existing personal relationships remains limited, while broader networks and experience are the key drivers. This consistency across settings, with and without choice set ambiguity, strengthens the case that the consideration set approach is both valid and robust, and suggests that the main findings are not driven by artifacts of unobserved or misspecified choice sets.

Consideration set models are suitable in numerous other settings in the Finance literature. When studying household investor behaviour, investor preferences, executive appointment & turnover, credit

[15] In estimations that are not reported in this paper, I find that these results are quantitatively similar when considering only connections to the CEO or only connections to non-CEO members of the board

[16] Because of simulation, and because an analytical gradient cannot be provided for consideration parameters.

markets or financial contagion, discrete choice models are already a common occurrence. Whether it is to simulate inattention, nonrandom choice sets, or brokered markets, consideration set models can help lower the bias of estimates at a reasonable computational cost[17].

[17] See Crawford et al. (2021) for a survey of such models, based on the notion of sufficient sets.

Bibliography

ABALUCK, J. AND A. ADAMS-PRASSL (2021): ''What do Consumers Consider Before They Choose? Identification from Asymmetric Demand Responses,'' *The Quarterly Journal of Economics*, 136, 1611–1663.

ACHARYA, V. V., R. S. CHAUHAN, R. RAJAN, AND S. STEFFEN (2023): ''Liquidity dependence and the waxing and waning of central bank balance sheets,'' Tech. rep., National Bureau of Economic Research.

ALBERTAZZI, U., B. BECKER, AND M. BOUCINHA (2018): ''Portfolio Rebalancing and the Transmission of Large-Scale Asset Programmes: Evidence from the Euro Area,'' *SSRN Journal*.

ALBERTAZZI, U., L. BURLON, T. JANKAUSKAS, AND N. PAVANINI (2022): ''The shadow value of unconventional monetary policy,'' *CEPR Discussion Paper No. DP17053*.

ALTAVILLA, C., G. CARBONI, AND R. MOTTO (2021): ''Asset Purchase Programs and Financial Markets: Lessons from the Euro Area,'' *International Journal of Central Banking*.

ARRATA, W. AND B. NGUYEN (2017): ''Price Impact of Bond Supply Shocks: Evidence from the Eurosystem's Asset Purchase Program,'' *SSRN Journal*.

ARRATA, W., B. NGUYEN, I. RAHMOUNI-ROUSSEAU, AND M. VARI (2020): ''The scarcity effect of QE on repo rates: Evidence from the euro area,'' *Journal of Financial Economics*, 137, 837–856.

BALLENSIEFEN, B., A. RANALDO, AND H. WINTERBERG (2023): ''Money Market Disconnect,'' *The Review of Financial Studies*.

BARROSO, J. ET AL. (2016): ''Quantitative easing and United States investor portfolio rebalancing towards foreign assets,'' *Banco Central Do Brasil Working Paper*.

BECHTEL, A., J. EISENSCHMIDT, A. RANALDO, AND A. V. VEGHAZY (2021): ''Quantitative Easing and the Safe Asset Illusion,'' *SSRN Electronic Journal*.

BEGENAU, J. AND T. LANDVOIGT (2022): ''Financial Regulation in a Quantitative Model of the Modern Banking System,'' *The Review of Economic Studies*, 89, 1748–1784.

BENETTON, M. (2021): ''Leverage Regulation and Market Structure: A Structural Model of the U.K. Mortgage Market,'' *The Journal of Finance*, 76, 2997–3053.

BERGER, A. N., T. KICK, M. KOETTER, AND K. SCHAECK (2013): ''Does it pay to have friends? Social ties and executive appointments in banking,'' *Journal of Banking & Finance*, 37, 2087–2105.

BERRY, S. (1994): ''Estimating Discrete-Choice Models of Product Differentiation,'' *The RAND Journal of Economics*, 25, 242–262.

BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): ''Automobile prices in market equilibrium,'' *Econometrica: Journal of the Econometric Society*, 841–890.

BIERLAIRE, M., T. LOTAN, AND P. TOINT (1997): ''On the overspecification of multinomial and nested logit models due to alternative specific constants,'' *Transportation Science*, 31, 363–371.

Bottero, M., C. Minoiu, J. L. Peydró, A. Polo, A. F. Presbitero, and E. Sette (2022): ''Expansionary yet different: Credit supply and real effects of negative interest rate policy,'' *Journal of Financial Economics*, 146, 754–778.

Bretscher, L., L. Schmid, I. Sen, and V. Sharma (2022): ''Institutional Corporate Bond Pricing,'' 75.

Brownstone, D. and P. Li (2018): ''A model for broad choice data,'' *Journal of Choice Modelling*, 27, 19–36.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018): ''Fintech, regulatory arbitrage, and the rise of shadow banks,'' *Journal of Financial Economics*, 130, 453–483.

——— (2024): ''Beyond the Balance Sheet Model of Banking: Implications for Bank Regulation and Monetary Policy,'' *Journal of Political Economy*, 132, 000–000.

Bundesbank, D. (2019): ''Longer-term changes in the unsecured interbank money market,'' Tech. rep., Bundesbank, Deutsche.

Cai, J., T. Nguyen, and R. Walkling (2021): ''Director Appointments: It Is Who You Know,'' *The Review of Financial Studies*.

Carpinelli, L. and M. Crosignani (2021): ''The design and transmission of central bank liquidity provisions,'' *Journal of Financial Economics*, 141, 27–47.

Cecchetti, S. and A. Kashyap (2018): ''What Binds? Interactions between Bank Capital and Liquidity Regulations,'' *The changing fortunes of central banking*, 192.

Chaudhary, M., Z. Fu, and J. Li (2022): ''Corporate Bond Elasticities: Substitutes Matter,'' .

Chaudhry, A. (2022): ''Do Subjective Growth Expectations Matter for Asset Prices?'' *Available at SSRN*.

Chen, W., S. Liang, and D. Shi (2022): ''What Drives Stock Prices in a Bubble?'' .

Christensen, J. H. and S. Krogstrup (2022): ''A portfolio model of quantitative easing,'' *The Quarterly Journal of Finance*, 12, 2250011.

Cohen, L. (2022): ''Examining QE's bang for the Buck: Does Quantitative easing reduce credit and liquidity risks and stimulate real economic activity?'' *Journal of International Financial Markets, Institutions and Money*, 79, 101596.

Corbae, D. and P. D. . Erasmo (2021): ''Capital Buffers in a Quantitative Model of Banking Industry Dynamics,'' *Econometrica*, 89, 2975–3023.

Crawford, G. S., R. Griffith, and A. Iaria (2021): ''A survey of preference estimation with unobserved choice set heterogeneity,'' *Journal of Econometrics*, 222, 4–43.

Crawford, G. S., N. Pavanini, and F. Schivardi (2018): ''Asymmetric Information and Imperfect Competition in Lending Markets,'' *American Economic Review*, 108, 1659–1701.

Darmouni, O. and K. Y. Siani (2022): ''Bond Market Stimulus: Firm-Level Evidence from 2020-21,'' 59.

D'Avernas, A. and Q. Vandeweyer (2023): ''Treasury Bill Shortages and the Pricing of Short-Term Assets,'' *The Journal of Finance*.

Davis, S. J. and J. Haltiwanger (1992): ''Gross Job Creation, Gross Job Destruction, and Employment Reallocation,'' *The Quarterly Journal of Economics*, 107, 819–863.

De Fiore, F., M. Hoerova, C. Rogers, and H. Uhlig (2024): ''Money markets, collateral and monetary policy,'' *NBER Working paper*.

Dell'Ariccia, G., L. Laeven, and R. Marquez (2014): ''Real interest rates, leverage, and bank risk-taking,'' *Journal of Economic Theory*, 149, 65–99.

Diamond, W., Z. Jiang, and Y. Ma (2024): ''The reserve supply channel of unconventional monetary policy,'' *Journal of Financial Economics*, 159, 103887.

Draganska, M. and D. Jain (2004): ''A Likelihood Approach to Estimating Market Equilibrium Models,'' *Management Science*, 50, 605–616.

Egan, M., A. Hortaçsu, and G. Matvos (2017): ''Deposit Competition and Financial Fragility: Evidence from the US Banking Sector,'' *American Economic Review*, 107, 169–216.

Eisenschmidt, J., Y. Ma, and A. L. Zhang (2024): ''Monetary policy transmission in segmented markets,'' *Journal of Financial Economics*, 151, 103738.

Fabo, B., M. Jancoková, E. Kempf, and L. Pástor (2021): ''Fifty Shades of QE: Comparing Findings of Central Bankers and Academics,'' 41.

Fahlenbrach, R., H. Kim, and A. Low (2018): ''The Importance of Network Recommendations in the Director Labor Market,'' *SSRN Journal*.

Fraisse, H., M. Lé, and D. Thesmar (2020): ''The Real Effects of Bank Capital Requirements,'' *Management Science*, 66, 5–23.

Fratzscher, M., M. Lo Duca, and R. Straub (2018): ''On the International Spillovers of US Quantitative Easing,'' *Econ J*, 128, 330–377.

Gabaix, X. and R. S. Koijen (2024): ''Granular instrumental variables,'' *Journal of Political Economy*, 132, 000–000.

Gabaix, X. and R. S. J. Koijen (2021): ''In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis,'' 120.

Gârleanu, N. and L. H. Pedersen (2013): ''Dynamic Trading with Predictable Returns and Transaction Costs,'' *Journal of Finance*, 68, 2309–2340.

Geweke, J. (1988): ''Antithetic acceleration of Monte Carlo integration in Bayesian inference,'' *Journal of Econometrics*, 38, 73–89.

GOEREE, M. S. (2008): ''Limited Information and Advertising in the U.S. Personal Computer Industry,'' *Econometrica*, 76, 1017–1074, publisher: [Wiley, Econometric Society].

GOLDSMITH-PINKHAM, P., I. SORKIN, AND H. SWIFT (2020): ''Bartik instruments: What, when, why, and how,'' *American Economic Review*, 110, 2586–2624.

GREENWOOD, R., J. C. STEIN, S. G. HANSON, AND A. SUNDERAM (2017): ''Strengthening and streamlining bank capital regulation,'' *Brookings Papers on Economic Activity*, 2017, 479–565.

GROMB, D. AND D. VAYANOS (2010): ''Limits of Arbitrage,'' *Annu. Rev. Financ. Econ.*, 2, 251–275.

HABIBI, S., E. FREJINGER, AND M. SUNDBERG (2019): ''An empirical study on aggregation of alternatives and its influence on prediction in car type choice models,'' *Transportation*, 46, 563–582.

HAUSMAN, J. A. (1994): *Valuation of new goods under perfect and imperfect competition*, National Bureau of Economic Research Cambridge, Mass., USA.

HAUSMAN, J. A. AND D. A. WISE (1978): ''A conditional probit model for qualitative choice: Discrete decisions recognizing interdependence and heterogeneous preferences,'' *Econometrica: Journal of the econometric society*, 403–426.

HERMALIN, B. E. AND M. S. WEISBACH (1988): ''The Determinants of Board Composition,'' *The RAND Journal of Economics*, 19, 589–606, publisher: [RAND Corporation, Wiley].

——— (1998): ''Endogenously chosen boards of directors and their monitoring of the CEO,'' *American Economic Review*, 96–118.

HOEROVA, M., C. MENDICINO, K. NIKOLOV, G. SCHEPENS, AND S. VAN DEN HEUVEL (2018): ''Benefits and Costs of Liquidity Regulation,'' *SSRN Electronic Journal*.

HONG, H., J. Z. HUANG, AND D. WU (2014): ''The information content of Basel III liquidity risk measures,'' *Journal of Financial Stability*, 15, 91–111.

HUEBNER, P. (2022): ''The Making of Momentum,'' .

KADLEC, G. B. AND J. J. MCCONNELL (1994): ''The effect of market segmentation and illiquidity on asset prices: Evidence from exchange listings,'' *The Journal of Finance*, 49, 611–636.

KASHYAP, A. K. AND J. C. STEIN (2012): ''The Optimal Conduct of Monetary Policy with Interest on Reserves,'' *American Economic Journal: Macroeconomics*, 4, 266–82.

KEANE, M. P. AND N. WASI (????): ''Estimation of Discrete Choice Models with Many Alternatives Using Random Subsets of the Full Choice Set: With an Application to Demand for Frozen Pizza,'' 33.

KHWAJA, A. I. AND A. MIAN (2008): ''Tracing the impact of bank liquidity shocks: Evidence from an emerging market,'' *American Economic Review*, 98, 1413–1442.

KLEIN, M. A. (1971): ''A theory of the banking firm,'' *Journal of money, credit and banking*, 3, 205–218.

KOIJEN, R. S., F. KOULISCHER, B. NGUYEN, AND M. YOGO (2021a): ''Inspecting the mechanism of quantitative easing in the euro area,'' *Journal of Financial Economics*, 140, 1–20.

——— (2021b): ‘‘Inspecting the mechanism of quantitative easing in the euro area,’’ *Journal of Financial Economics*, 140, 1–20.

KOIJEN, R. S., R. J. RICHMOND, AND M. YOGO (2020): ‘‘Which investors matter for equity valuations and expected returns?’’ Tech. rep., National Bureau of Economic Research.

KOIJEN, R. S. AND M. YOGO (2020): ‘‘Exchange rates and asset prices in a global demand system,’’ Tech. rep., National Bureau of Economic Research.

KOIJEN, R. S. J., F. KOULISCHER, B. NGUYEN, AND M. YOGO (2017): ‘‘Euro-Area Quantitative Easing and Portfolio Rebalancing,’’ *American Economic Review*, 107, 621–627.

KOIJEN, R. S. J. AND M. YOGO (2016): ‘‘Shadow Insurance,’’ *Econometrica*, 84, 1265–1287.

——— (2019): ‘‘A Demand System Approach to Asset Pricing,’’ *Journal of Political Economy*, 42.

——— (2022): ‘‘Understanding the Ownership Structure of Corporate Bonds,’’ *VOL. NO.*, 23.

KOONT, N. (2023): ‘‘The digital banking revolution: Effects on competition and stability,’’ *Available at SSRN*.

KRAMARZ, F. AND D. THESMAR (2013): ‘‘Social networks in the boardroom,’’ *Journal of the European Economic Association*, 11, 780–807.

LIU, Y. (2010): ‘‘The role of networks in the CEO and director labor market,’’ Ph.D. thesis.

MABIT, S. L. (2011): ‘‘Vehicle type choice and differentiated registration taxes,’’ in *ETC 2011*.

MARKOWITZ, H. M. (1952): ‘‘Portfolio Selection,’’ *Journal of Finance*, 7, 7791.

MARTIN, A., J. MCANDREWS, A. PALIDA, AND D. R. SKEIE (2019): ‘‘Federal Reserve Tools for Managing Rates and Reserves,’’ *SSRN Electronic Journal*.

MARTINS, L. F., J. BATISTA, AND A. FERREIRA-LOPES (2019): ‘‘Unconventional monetary policies and bank credit in the Eurozone: An events study approach,’’ *International Journal of Finance and Economics*, 24, 1210–1224.

MCFADDEN, D. (1973): ‘‘Conditional logit analysis of qualitative choice behavior,’’ .

——— (1974): ‘‘Conditional logit analysis of qualitative choice behavior,’’ *Frontiers in econometrics*.

——— (2001): ‘‘Economic choices,’’ *American economic review*, 91, 351–378.

MERTON, R. C. ET AL. (1987): ‘‘A simple model of capital market equilibrium with incomplete information,’’ .

MONTI, M. ET AL. (1972): *Deposit, credit and interest rate determination under alternative bank objective function*, North-Holland/American Elsevier Amsterdam.

MURDOCK, J. (2006): ‘‘Handling unobserved site characteristics in random utility models of recreation demand,’’ *Journal of Environmental Economics and Management*, 51, 1–25.

NEVO, A. (2001a): ''Measuring market power in the ready-to-eat cereal industry,'' *Econometrica*, 69, 307–342.

——— (2001b): ''Measuring Market Power in the Ready-to-Eat Cereal Industry,'' *Econometrica*, 69, 307–342, publisher: [Wiley, Econometric Society].

PALUDKIEWICZ, K. (2021): ''Unconventional Monetary Policy, Bank Lending, and Security Holdings: The Yield-Induced Portfolio-Rebalancing Channel,'' *Journal of Financial and Quantitative Analysis*, 56, 531–568.

PERIGNON, C., D. THESMAR, AND G. VUILLEMEY (2018): ''Wholesale Funding Dry-Ups,'' *The Journal of Finance*, 73, 575–617.

PEYDRÓ, J. L., A. POLO, AND E. SETTE (2021): ''Monetary policy at work: Security and credit application registers evidence,'' *Journal of Financial Economics*, 140, 789–814.

ROGERS, C. (2022): ''Quantitative Easing and Local Banking Systems in the Euro Area,'' *Working Paper*.

ROSEN, S. (1974): ''Hedonic prices and implicit markets: product differentiation in pure competition,'' *Journal of political economy*, 82, 34–55.

ROSENSTEIN, S. AND J. G. WYATT (1990): ''Outside directors, board independence, and shareholder wealth,'' *Journal of financial economics*, 26, 175–191.

SHARPE, W. F. (1964): ''Capital asset prices: A theory of market equilibrium under conditions of risk,'' *The journal of finance*, 19, 425–442.

SIANI, K. (2022): ''Raising Bond Capital in Segmented Markets,'' 74.

SUDO, N. AND M. TANAKA (2021): ''Quantifying Stock and Flow Effects of QE,'' *Journal of Money, Credit and Banking*, 53, 1719–1755.

SUNDARESAN, S. AND K. XIAO (2024): ''Liquidity regulation and banks: Theory and evidence,'' *Journal of Financial Economics*, 151, 103747.

TOBIN, J. (1969): ''A general equilibrium approach to monetary theory,'' *Journal of money, credit and banking*, 1, 15–29.

TODOROV, K. (2020): ''Quantify the quantitative easing: Impact on bonds and corporate debt issuance,'' *Journal of Financial Economics*, 135, 340–358.

VAN DER BECK, P. (2021): ''Flow-Driven ESG Returns,'' *SSRN Journal*.

——— (2022): ''On the Estimation of Demand-Based Asset Pricing Models,'' .

VAYANOS, D. AND J.-L. VILA (2021): ''A Preferred-Habitat Model of the Term Structure of Interest Rates,'' *ECTA*, 89, 77–112.

——— (2023): ''A Preferred-Habitat Model of the Term Structure of Interest Rates,'' *Econometrica*, 91, 31–32.

Walz, S. (2024): ''Monetary Policy Complementarity: Bank Regulation and the Term Premium,'' *Available at SSRN*.

Wang, J. X. (2020): ''Board Connections and CEO succession,'' *Available at SSRN 3551748*.

Wang, Y., T. M. Whited, Y. Wu, and K. Xiao (2022): ''Bank Market Power and Monetary Policy Transmission: Evidence from a Structural Estimation,'' *Journal of Finance*, 77, 2093–2141.

Wong, T., D. Brownstone, and D. S. Bunch (2019): ''Aggregation biases in discrete choice models,'' *Journal of Choice Modelling*, 31, 210–221.

Xiao, K. (2021): ''Monetary transmission through shadow banks,'' .

3.A The general model is unidentified

Let us denote firms by i, individual directors by k, and the set of individuals sharing observables x_j as B_j.

Let us consider a pairing between a firm i and a director k with observables $x_k = x_j$. Assume that this match generates the following utility, that is fully captured by the firm.

$$u_{ijk} = V_{ij} + \omega_{ik} + \epsilon_{ijk}$$

With V_{ij} the match utility from observables x_j, ω_{ik} the match utility from unobservables of individual k, and ϵ_{ijk} the idiosyncratic component of utility. Under standard assumptions on the distribution of ϵ (Gumbel extreme value) and normalizing the outside option, we get the following choice probabilities

$$\begin{aligned}\mathbb{P}_{ij} &= \frac{\sum_{k \in B_j} e^{V_{ij}+\omega_{ik}}}{1 + \sum_l \sum_{k \in B_l} e^{V_{il}+\omega_{ik}}} \\ &= \frac{e^{V_{ij}+\Omega_{ij}}}{1 + \sum_l e^{V_{il}+\Omega_{il}}}\end{aligned}$$

Where $\Omega_{ij} = \ln \sum_{k \in B_j} e^{\omega_{ik}}$. It is quite clear that Ω_{ij} cannot be identified without further assumptions. However, making assumptions on Ω_{ij} amounts to making assumptions on the distribution of ω_{ik} and on the distribution of $Card(B_j)$. The problem is well known in the consumer choice literature (Hausman and Wise, 1978) and it has been shown that while aggregation by averaging over observables may bias down the estimates and increase standard errors (Mabit (2011), Habibi et al. (2019)), aggregation ignoring hidden heterogeneity is even more problematic (Brownstone and Li (2018), Wong et al. (2019)).

3.B Estimation Procedure

Remember that we wish to approximate the likelihood

$$\prod_i \sum_j \mathbf{1}(y_i = j) \cdot p_{ij}(\theta) = \prod_i \sum_j \mathbf{1}(y_i = j) \cdot \sum_C \prod_{l \in C} \phi_{il} \prod_{k \notin C} (1 - \phi_{ik}) \mathbb{P}_{ij}(x_j, z_i | C, \theta)$$

Where $\mathbf{1}(y_i = j)$ is the indicator function taking a value of 1 whenever firm i chose profile j, and θ is the vector of parameters.. This is computationally unfeasible, as it would require us to sum over all possible choice sets C, or at least over the subset of choice sets C_j including option j. As there are more than 800 different profiles, this represents over an overwhelming number of possible combinations.

The obvious solution is to use numerical simulation. We have

$$p_{ij} = \sum_C \prod_{l \in C} \phi_{il} \prod_{k \notin C} (1 - \phi_{ik}) \mathbb{P}_{ij}(x_j, z_i | C, \theta) \simeq \frac{\sum_{r=1}^R \mathbb{P}_{ij}(x_j, z_i | C_r, \theta)}{R}$$

$$\text{with } C_r \sim \prod_{l \in C} \phi_{il} \prod_{k \notin C} (1 - \phi_{ik})$$

For R large enough, we have a good approximation of p_{ij}. Fortunately, when using antithetic covariates, we can achieve a good approximation for a relatively small number of simulations R. Unfortunately, when R is relatively small, this approximation is not smooth: a change in parameters θ may lead to a change in consideration probabilities $\prod_{l \in C} \phi_{il} \prod_{k \notin C} (1 - \phi_{ik})$ that leads to a vastly different choice set. Then, the choice probabilities can jump, as the choice set is different: an infinitely small change in parameters θ may lead to an abrupt change in value.

I follow the solution proposed in Goeree (2008), and I implement an importance sampling to resolve this issue. For ease of notation, let us denote

$$\Phi(C|\theta) = \prod_{l \in C} \phi_{il}(\theta) \prod_{k \notin C} (1 - \phi_{ik}(\theta))$$

We have

$$p_{ij}(\theta) = \sum_C \Phi(C|\theta) \cdot \mathbb{P}_{ij}(x_j, z_i | C, \theta)$$

We can rewrite the equation using Φ evaluated at the initial guess of parameters, θ^0

$$p_{ij}(\theta) = \sum_C \frac{\Phi(C|\theta)}{\Phi(C|\theta^0)} \cdot \Phi(C|\theta^0) \cdot \mathbb{P}_{ij}(x_j, z_i | C, \theta)$$

Therefore,

$$p_{ij} \simeq \frac{1}{R} \sum_r \frac{\Phi(C_r|\theta)}{\Phi(C_r^0|\theta^0)} \cdot \mathbb{P}_{ij}(x_j, z_i | C_r^0, \theta)$$

with $C_r^0 \sim \Phi(C|\theta^0); C_r \sim \Phi(C|\theta)$ drawn from the same underlying uniform distribution[18].

As the choice probabilities are evaluated over the initial choice sets, there is no jump in probabilities when

[18] That is, $C_r^0 \sim \Phi(C|\theta^0); C_r \sim \Phi(C|\theta)$ are drawn as transformations of the same draw from the uniform distribution, drawn once and for all at the beginning of the procedure.

the realised choice set changes, as this only affects the ratio $\Phi(C_r|\theta)/\Phi(C_r^0|\theta^0)$, which is much smoother. This allows the standard optimisation procedures to work their magic and converge to consistent estimates.

The estimation proceeds as follows:

1. To set up the initial choice set
   (a) Draw R uniform random variables u_{ijr} over $\mathcal{U}_{0,1}$ for each firm-profile pair (i, j). These draws will remain fixed for the duration of the estimation to ensure consistent convergence.
   (b) Draw their antithetic covariates $u_{ij-r} = 1 - u_{ijr}$, to obtain $2R$ draws for each firm-profile pair.
   (c) Set an initial value θ^0 for parameters.
   (d) Calculate $\phi_{ij}(\theta^0)$ for each firm-profile pair.
   We will store the $\phi_{ij}(\theta^0)$ and u_{ij} in memory for the rest of the estimation.
   (e) For each firm, define the $2R$ choice sets C_{ir}^0 such that

$$j \in C_{ir}^0 \Leftrightarrow \phi_{ij}(\theta^0) > u_{ijr}$$

2. At each iteration:
   (a) Calculate $\phi_{ij}(\theta)$ for each firm-profile pair.
   (b) For each firm, define the $2R$ choice sets C_{ir} such that

$$j \in C_{ir} \Leftrightarrow \phi_{ij}(\theta) > u_{ijr}$$

   (c) Compute

$$\mathbb{P}_{ij}(x_j, z_i|C_r^0, \theta)$$

   (d) Calculate

$$\begin{aligned} p_{ij}(\theta) &\simeq \frac{1}{2R}\sum_{r=-R}^{R}\frac{\Phi(C_r|\theta)}{\Phi(C_r^0|\theta^0)}\cdot\mathbb{P}_{ij}(x_j, z_i|C_r^0, \theta) \\ &\simeq \frac{1}{2R}\sum_{r=-R}^{R}\frac{\prod_{l\in C_{ir}}\phi_{il}(\theta)\prod_{k\notin C_{ir}}(1-\phi_{ik}(\theta))}{\prod_{l\in C_{ir}^0}\phi_{il}(\theta^0)\prod_{k\notin C_{ir}^0}(1-\phi_{ik}(\theta^0))}\cdot\mathbb{P}_{ij}(x_j, z_i|C_r^0, \theta) \end{aligned}$$

   Note that the choice set will change over time, but this will only be taken into account in $\Phi(C_r|\theta)$. $\mathbb{P}$ will be evaluated over the initial choice set using the updated parameter values θ, and $\Phi(C_r^0|\theta^0)$ will remain constant over the course of the estimation.
   (e) The log-likelihood is calculated as usual

$$LogLik = \sum_i \ln\left(\sum_j \mathbf{1}(y_i = j)\cdot p_{ij}(\theta)\right)$$

3. Iterate until convergence.

3.C Model Fit

Below is displayed a table showing the fit of the model.

- Distance: Less is better
- Fit: More is better, max = 1

3.D Tables

Table 3.11: Compensation Committee Appointments

This table displays the result of the estimation for the committee appointments. The dependent variable is the likelihood for a board to appoint a given director to the Audit Committee. The choice set is composed of all members of the board apart from the CEO. The first column displays the estimates, the second column displays the t-statistic and the fourth column displays the significance level (*=10%, **=5%, ***=1%) The Gender variable takes a value of 1 for men and 0 for women.

Interaction	Estimate	t-stat	p-value
Board size-Intercept	-0.46^{***}	-30.71	
Size-Intercept	-0.02	-0.77	
ROA-Intercept	0.65^{***}	3.53	
Board Network-Intercept	0.81^{***}	17.17	
Leverage-Intercept	0.04^{**}	1.98	
Intercept-Intercept	-7.17^{***}	-18.20	
Board Size - Contacts at nomination	0.03^{***}	15.00	
Size - Contacts at nomination	-0.01^{***}	-2.71	
ROA - Contacts at nomination	-0.01	-0.15	
Board Network - Contacts at nomination	0.02^{**}	2.03	
Leverage - Contacts at nomination	0.00	-0.55	
Intercept - Contacts at nomination	-0.30^{***}	-3.93	
Mean:	-0.08		
Board Size - Network Size	0.07^{***}	17.40	
Size - Network Size	0.08^{***}	9.72	
ROA - Network Size	-0.25^{***}	-4.34	
Board Network - Network Size	-0.43^{***}	-27.29	
Leverage - Network Size	-0.08	-1.49	
Intercept - Network Size	3.32^{***}	25.14	
Mean:	0.45		
Gender	-0.23^{***}	-11.43	
Age	-0.01^{***}	-9.62	
Supervisory	4.35^{***}	67.39	
Bachelor	0.02	1.22	
MBA	0.00	-0.10	
GraduateDegree	-0.07^{***}	-4.69	
Experience	-0.21^{***}	-9.89	
Nobservations	33400	Log-Likelihood	-49938

	Base Model Distance	Base Model Fit	Consideration Model Distance	Consideration Model Fit
Manhattan Distance	0.624	0.500	0.345	0.723
Euclidian Distance	0.057	0.452	0.033	0.680

Table 3.12: Summary Statistics
This table provides descriptive statistics for the firm variables. These variables have been winsorized at the 2.5% and the 97.5% level.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
boardsize	69843	7.501	3.296	0	5	9	33
ROA	69843	0.002	0.247	-1.428	-0.015	0.098	0.463
Size	69843	6.654	2.275	1.6	5.061	8.167	12.495
leverage	69843	0.974	2.56	-7.354	0.044	1.153	17.537
Q	69843	0.933	0.958	0.249	0.579	0.931	7.964
Industries	69843	0.407	0.809	0	0	1	10
Board Network	69843	8.738	1.458	3.219	8.062	9.677	12.634
NEWCEO	69843						
... No	43265	61.9%					
... Yes	26578	38.1%					
SupervisoryDirector	69843						
... No	10550	15.1%					
... Yes	59293	84.9%					

Table 3.13: Summary Statistics
This table provides distribution of the profile variables, when an outsider director has been given the directorship. For the 9950 observations where an insider director has been recruited rather than an outsider, these values (as well as the value of the intercept) are set to 0.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
ncontacts	64615	0.316	0.828	0	0	0	4
networksize	64615	2.36	0.673	1	2	3	4
ages	64615	55.071	8.657	40	50	60	70
experience	64615						
... No	56362	87.2%					
... Yes	8253	12.8%					
Bachelor	64615						
... No	25519	39.5%					
... Yes	39096	60.5%					
MBA	64615						
... No	43718	67.7%					
... Yes	20897	32.3%					
Graduate	64615						
... No	49274	76.3%					
... Yes	15341	23.7%					
JD	64615						
... No	56946	88.1%					
... Yes	7669	11.9%					

Table 3.14: Impact of Industry Experience.

This table presents the results from the baseline model estimation. The dependent variable is the likelihood that a firm appoints a director with the observed appointee's profile. The first column reports the raw estimate for the impact of past industry experience at the 3-digit SIC level, interacted with the indicated firm characteristic, on u_{ij}. The second column shows the effect of a one standard deviation change in the firm characteristic (estimate × standard deviation). The third column reports the t-statistic, and the fourth column indicates the significance level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

	Estimates	Std Effect	t-stat	
boardsize	-0.04	-0.13	-6.23	***
ROA	0.01	0.00	0.25	
Size	-0.01	-0.02	-0.77	
M2B	0.01	0.07	5.34	***
leverage	-0.04	-0.11	-7.33	***
Q	0.10	0.09	7.05	***
Industries	-0.47	-0.38	-22.65	***
NEWCEO	0.36	0.18	13.78	***
Board Network	0.46	0.68	31.39	***
Supervisory Director	-0.04	-0.01	-0.81	
Intercept	-5.64		-44.52	***
Mean effect of industry experience	-1.914566			
Number of observations	69843			
Log-Likelihood	-130696.2	Pseudo R^2	0.3922	

Table 3.15: Consideration Set Estimation Results, I

Interaction ($z_i \cdot x_j$)	**Estimate**	**Std Effect**	**p-value**
boardsize-ages	-9.20×10^{-5}	-3.03×10^{-4}	0.767
deviationfrommeanROA-ages	-4.13×10^{-4}	-1.02×10^{-4}	0.925
logat-ages	$4.55 \times 10^{-3***}$	1.04×10^{-2}	0.00
leverage-ages	-5.51×10^{-4} *	-1.41×10^{-3}	0.079
Q-ages	1.09×10^{-3}	1.04×10^{-3}	0.352
IndustriesSpanning-ages	1.27×10^{-3}	1.03×10^{-3}	0.223
NEWCEO-ages	-1.09×10^{-3}	-5.28×10^{-4}	0.555
SupervisoryDirector-ages	$5.92 \times 10^{-2***}$	2.12×10^{-2}	0.00
Intercept-ages	$-7.70 \times 10^{-2***}$	0.00	0.00
boardsize-experience	$-7.27 \times 10^{-2***}$	-2.40×10^{-1}	2.99×10^{-9}
deviationfrommeanROA-experience	-1.59×10^{-1}	-3.91×10^{-2}	0.460
logat-experience	$-7.48 \times 10^{-2***}$	-1.70×10^{-1}	8.76×10^{-4}
leverage-experience	$-3.36 \times 10^{-2**}$	-8.59×10^{-2}	0.021
Q-experience	1.70×10^{-1}	1.63×10^{-1}	0.084
IndustriesSpanning-experience	$-7.59 \times 10^{-2**}$	-6.14×10^{-2}	0.024
NEWCEO-experience	$5.56 \times 10^{-1***}$	2.70×10^{-1}	0.00
SupervisoryDirector-experience	$8.34 \times 10^{-1***}$	2.98×10^{-1}	0.00
Intercept-experience	5.71 ***	0.00	0.00
boardsize-MBA	$1.45 \times 10^{-2**}$	4.77×10^{-2}	0.028
deviationfrommeanROA-MBA	-8.86×10^{-2}	-2.19×10^{-2}	0.329
logat-MBA	$9.64 \times 10^{-2***}$	2.19×10^{-1}	0.00
leverage-MBA	-2.10×10^{-3}	-5.39×10^{-3}	0.740
Q-MBA	-6.64×10^{-3}	-6.36×10^{-3}	0.796
IndustriesSpanning-MBA	1.01×10^{-2}	8.20×10^{-3}	0.614
NEWCEO-MBA	$1.91 \times 10^{-1***}$	9.27×10^{-2}	2.06×10^{-7}
SupervisoryDirector-MBA	$-2.78 \times 10^{-1***}$	-9.94×10^{-2}	0.00
Intercept-MBA	-1.86^{***}	0.00	0.00
boardsize-JD	$2.80 \times 10^{-2***}$	9.23×10^{-2}	0.0003
deviationfrommeanROA-JD	-5.81×10^{-2}	-1.43×10^{-2}	0.625
logat-JD	$8.79 \times 10^{-2***}$	2.00×10^{-1}	0.00
leverage-JD	$1.62 \times 10^{-2**}$	4.16×10^{-2}	0.040
Q-JD	$9.76 \times 10^{-2***}$	9.36×10^{-2}	0.0048
IndustriesSpanning-JD	$6.56 \times 10^{-2***}$	5.31×10^{-2}	0.0062
NEWCEO-JD	-2.46×10^{-2}	-1.20×10^{-2}	0.594
SupervisoryDirector-JD	-5.01×10^{-2}	-1.79×10^{-2}	0.487
Intercept-JD	-3.88^{***}	0.00	0.00
boardsize-networksize	$-9.08 \times 10^{-2***}$	-2.99×10^{-1}	0.00
deviationfrommeanROA-networksize	$1.48 \times 10^{-1**}$	3.66×10^{-2}	0.032
logat-networksize	-1.41×10^{-2}	-3.20×10^{-2}	0.082
leverage-networksize	-5.93×10^{-3}	-1.52×10^{-2}	0.233
Q-networksize	$-5.17 \times 10^{-2**}$	-4.95×10^{-2}	0.011
IndustriesSpanning-networksize	$5.30 \times 10^{-2***}$	4.28×10^{-2}	0.0011
NEWCEO-networksize	1.58×10^{-2}	7.65×10^{-3}	0.586
SupervisoryDirector-networksize	$9.24 \times 10^{-1***}$	3.31×10^{-1}	0.00
Intercept-networksize	2.84^{***}	0.00	0.00

Notes: This table displays the result of the Consideration set Estimation. The dependent variable is the likelihood for a firm to appoint a director with the observed appointee's profile. The first column displays the raw estimates, the second column displays the impact of a standard deviation in firm characteristic on u_{ij} (estimate × standard deviation of the characteristic), the third column displays the t-statistic and the fourth column displays the significance level (*=10%, **=5%, ***=1%).
Number of observations: 69,843; Log-Likelihood: −68,523.18.

Table 3.16: Consideration Set Estimation Results, II

Interaction ($z_i \cdot x_j$)	**Estimate**	**Std Effect**	**p-value**
boardsize-ncontacts	$4.63 \times 10^{-2***}$	1.53×10^{-1}	0.00
deviationfrommeanROA-ncontacts	-7.28×10^{-2}	-1.80×10^{-2}	0.062
logat-ncontacts	-5.19×10^{-3}	-1.18×10^{-2}	0.196
leverage-ncontacts	$1.63 \times 10^{-2***}$	4.16×10^{-2}	0.00
Q-ncontacts	$6.61 \times 10^{-2***}$	6.34×10^{-2}	0.00
IndustriesSpanning-ncontacts	$-1.43 \times 10^{-1***}$	-1.15×10^{-1}	0.00
NEWCEO-ncontacts	$7.62 \times 10^{-2***}$	3.70×10^{-2}	1.67×10^{-8}
SupervisoryDirector-ncontacts	$-1.56 \times 10^{-1***}$	-5.57×10^{-2}	0.00
Intercept-ncontacts	-1.76^{***}	0.00	0.00
boardsize-Bachelor	$-2.39 \times 10^{-2***}$	-7.87×10^{-2}	0.00093
deviationfrommeanROA-Bachelor	$-2.45 \times 10^{-1**}$	-6.06×10^{-2}	0.032
logat-Bachelor	$1.21 \times 10^{-1***}$	2.74×10^{-1}	0.00
leverage-Bachelor	$-1.83 \times 10^{-2**}$	-4.68×10^{-2}	0.021
Q-Bachelor	-4.33×10^{-2}	-4.15×10^{-2}	0.155
IndustriesSpanning-Bachelor	$1.08 \times 10^{-1***}$	8.76×10^{-2}	2.77×10^{-5}
NEWCEO-Bachelor	$2.96 \times 10^{-1***}$	1.44×10^{-1}	0.00
SupervisoryDirector-Bachelor	$5.44 \times 10^{-1***}$	1.95×10^{-1}	2.15×0.00
Intercept-Bachelor	1.52×10^{-1}	0.00	0.126
boardsize-Graduate	-2.04×10^{-3}	-6.72×10^{-3}	0.802
deviationfrommeanROA-Graduate	-1.56×10^{-1}	-3.86×10^{-2}	0.198
logat-Graduate	$1.34 \times 10^{-1***}$	3.05×10^{-1}	0.00
leverage-Graduate	$-4.15 \times 10^{-2***}$	-1.06×10^{-1}	3.46×10^{-6}
Q-Graduate	8.36×10^{-3}	8.01×10^{-3}	0.800
IndustriesSpanning-Graduate	$9.92 \times 10^{-2***}$	8.02×10^{-2}	0.00031
NEWCEO-Graduate	$2.59 \times 10^{-1***}$	1.26×10^{-1}	8.82×10^{-8}
SupervisoryDirector-Graduate	$4.95 \times 10^{-1***}$	1.77×10^{-1}	0.00
Intercept-Graduate	-1.46^{***}	0.00	0.00
boardsize-Intercept	$-7.51 \times 10^{-2***}$	-2.47×10^{-1}	0.00024
deviationfrommeanROA-Intercept	2.05×10^{-1}	5.06×10^{-2}	0.457
logat-Intercept	$-5.84 \times 10^{-1***}$	-1.33	7.36×10^{-64}
leverage-Intercept	$1.33 \times 10^{-1***}$	3.40×10^{-1}	0.00
Q-Intercept	2.19×10^{-2}	2.10×10^{-2}	0.768
IndustriesSpanning-Intercept	$-2.03 \times 10^{-1**}$	-1.64×10^{-1}	0.0042
NEWCEO-Intercept	$-4.56 \times 10^{-1***}$	-2.21×10^{-1}	0.00019
SupervisoryDirector-Intercept	-2.28×10^{-2}	-8.16×10^{-3}	0.895
Intercept-Intercept	2.77^{***}	0.00	0.00
Consideration: logBoardNetwork-ncontacts	$9.77 \times 10^{-2***}$	2.02×10^{-1}	0.00
Consideration: Intercept-ncontacts	-0.17^{***}	-0.25	0.00
Consideration: logBoardNetwork-networksize	$8.83 \times 10^{-2***}$	2.14×10^{-1}	0.00
Consideration: Intercept-networksize	-0.19^{***}	-0.18	0.00
Consideration: logBoardNetwork-experience	0.46^{***}	0.35	0.00
Consideration: Intercept-experience	-0.055^{***}	-0.047	0.00
Consideration: logBoardNetwork-Intercept	0.29^{***}	0.11	1.68×0.00
Consideration: Intercept-Intercept	-0.12^{***}	0.00	0.00

Notes: This table displays the result of the Consideration set Estimation. The dependent variable is the likelihood for a firm to appoint a director with the observed appointee's profile. The first column displays the raw estimates, the second column displays the impact of a standard deviation in firm characteristic on u_{ij} (estimate × standard deviation of the characteristic), the third column displays the t-statistic and the fourth column displays the significance level (*=10%, **=5%, ***=1%).
Number of observations: 69,843; Log-Likelihood: −68,523.18.